Decision and Estimation in Data Processing

Chapter II. Elements of Signal Detection Theory

II.1 Introduction

Introduction

- Signal detection = the problem of deciding which signal is present from 2 or more possibilities
  - one possibility may be that there is no signal
- Based on **noisy** observations
  - signals are affected by noise

The model for signal detection

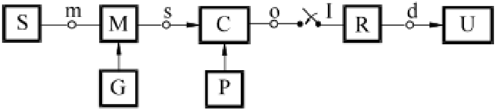

Figure 1: Signal detection model

- Contents:
  - Information source: generates messages a_n with probabilities $p(a_n)$
  - Modulator: transmits a signal $s_n(t)$ for message a_n
  - Channel: adds random noise
  - Sampler: takes samples from the signal $s_n(t)$
  - Receiver: **decides** what message a_n has been transmitted

Practical scenarios

- Data transmission
  - constant voltage levels (e.g. $s_n(t) =$ constant)
  - PSK modulation (Phase Shift Keying): $s_n(t) =$ cosine with same frequency but various initial phase
  - FSK modulation (Frequency Shift Keying): $s_n(t) =$ cosines with different frequencies
  - OFDM modulation (Orthogonal Frequency Division Multiplexing): particular case of FSK
- Radar
  - a signal is emitted; if there is an obstacle, the signal gets reflected back
  - the receiver waits for possible reflections of the signal and must decide
    - no reflection is present -> no object
    - reflected signal is present -> object detected

Generalizations

- Decide between more than two signals
- Number of observations:
  - use only one sample
  - use multiple samples
  - observe the whole continuous signal for some time T

II.2 Detection of constant signals based on 1 sample

Detection of a constant signal, 1 sample

- Simplest case: detection of a constant signal contaminated with white normal noise, using 1 sample
  - two messages a_0 and a_1
  - messages are encoded as constant signals
    - for a_0: send $s_0(t) = 0$
    - for a_1: send $s_1(t) = A$
  - over the signals there is additive noise
  - receiver takes just 1 sample
  - decision: compare sample with a threshold

Threshold-based decision

- The value of the sample taken is $r = s + n$
  - s is the true underlying signal ($s_0 = 0$ or $s_1 = A$)
  - n is a sample of the noise
- n is a (continuous) random variable
- r is a random variable also
  - what distribution does r have compared to n?
- Decision is taken by comparing with a threshold T:
  - if $r < T$, take decision D_0: decide the true signal is s_0
  - if $r \geq T$, take decision D_1: decide the true signal is s_1

Hypotheses

- Receiver chooses between **two hypotheses**:
  - H_0: true signal is s_0 (a_0 has been transmitted)
  - H_1: true signal is s_1 (a_1 has been transmitted)
- Possible results
  1. Correct rejection: no signal present, no signal detected.
     - Decision D_0 when hypothesis is H_0
     - Probability is $P_n = P(D_0 \cap H_0)$
  2. **False alarm**: no signal present, signal detected (error)
     - Decision D_1 when hypothesis is H_0
     - Probability is $P_{fa}P(D_1 \cap H_0)$
  3. **Miss**: signal present, no signal detected (error)
     - Decision D_0 when hypothesis is H_1
     - Probability is $P_m = P(D_0 \cap H_1)$
  4. **Hit**: signal present, signal detected
     - Decision D_1 when hypothesis is H_1
     - Probability is $P_d = P(D_1 \cap H_1)$

Maximum likelihood criterion

- Choose the hypothesis that **seems most likely** given the observed sample r
- The **likelihood** of an observation r = the probability density of r given a hypothesis H_0 or H_1
- Likelihood in case of hypothesis H_0: $w(r|H_0)$
  - r is only noise, so value is taken from the noise distribution
- Likelihood in case of hypothesis H_1: $w(r|H_1)$
  - r is A + noise, so value is taken from the distribution of (A + noise)
- **Likelihood ratio** test:

$$\frac{w(r|H_1)}{w(r|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} 1$$

Graphical interpretation

- Consider noise having a normal distribution
- Plot the two density functions for H_0, H_1

Decision via threshold

- Likelihood ratio test for ML $=$ comparing r with a threshold T
- The threshold $=$ the cross-over point of the two distributions

Normal noise

- Particular case: the noise has normal distribution $\mathcal{N}(0, \sigma^2)$
- Likelihood ratio is $\frac{w(r|H_1)}{r|H_0} = \frac{e^{-\frac{(r-A)^2}{2\sigma^2}}}{e^{-\frac{r^2}{2\sigma^2}}} \underset{H_0}{\overset{H_1}{\gtrless}} 1$
- For normal distribution, it is easier to apply *natural logarithm* to the terms
  - logarithm is a monotonic increasing function, so it won't change the comparison
  - if $A < B$, then $\log(A) < \log(B)$
- The **log-likelihood** of an observation = the logarithm of the likelihood value
  - usually the natural logarithm, but any one can be used

Log-likelihood test for ML

- For normal noise, the ML decision means the log-likelihood test

$$\frac{(r-A)^2}{r^2} \underset{H_0}{\overset{H_1}{\gtrless}} 1$$

- Applying square root

$$\frac{|r-A|}{|r|} \underset{H_0}{\overset{H_1}{\gtrless}} 1$$

- $|r-A|$ = distance from r to A, $|r|$ = distance from r to 0
- ML decision with normal noise: choose the value 0 or A which is **nearest** to r
  - very general principle, encountered in many other scenarios
  - also known as **nearest neighbor** principle / decision
  - ML receiver is also known as **minimum distance receiver**
  - equivalent with setting a threshold $T = \frac{A}{2}$

Generalizations

- What if the noise has another distribution?
  - Threshold T is still the cross-over point, whatever that is
  - There can be more cross-overs, so multiple thresholds
  - Can think that $\mathbb{R}$ axis is split into **decision regions** R_0 and R_1
- What if the noise distributions are different for H_0 and H_1?
  - Threshold T is the cross-over point, whatever that is
- What if the signal $s_0(t)$ (for H_0) is not 0, but another constant value B?
  - T is the crossover point, the distributions are centered on B and A
  - In case of normal noise, choose B or A whichever is nearest (threshold is at middle point)

Generalizations

- What if we have more than two signal levels?
  - e.g. 4 possible signals: -6, -2, 2, 6
  - Just choose the most likely hypothesis, out of 4 likelihood functions
  - Not a single threshold value, now there are more

Exercises

- A signal can have two possible values, 0 or 5. The receiver takes one sample with value $r = 2.25$
  1. Considering that the noise is white gaussian noise, what signal is decided based on the Maximum Likelihood criterion?
  2. What if the signal 0 is affected by gaussian noise $\mathcal{N}(0, 0.5)$, while the signal 5 is affected by uniform noise $\mathcal{U}[-4, 4]$?
  3. Repeat a. and b. assuming the value 0 is replaced by -1
- A signal can have four possible values: -6, -2, 2, 6. Each value lasts for 1 second. The signal is affected by white noise with normal distribution. The receiver takes 1 sample per second. Using ML criterion, decide what signal has been transmitted, if the received samples are:

$$4, 6.6, -5.2, 1.1, 0.3, -1.5, 7, -7, 4.4$$

Computing conditional error probabilities

- We can compute the conditional probabilities of errors
- Consider the decision regions:
  - R_0: when $r \in R_0$, decision is D_0, i.e. (∞, T) for gaussian noise
  - R_1: when $r \in R_1$, decision is D_1, i.e. $[T, \infty)$ for gaussian noise
- Probability of false alarm ***if*** *original signal is* $s_0(t)$

$$P(D_1|H_0) = \int_{R_1} w(r|H_0)dx$$

- Probability of miss ***if*** *original signal is* $s_1(t)$

$$P(D_0|H_1) = \int_{R_0} w(r|H_1)dx$$

- These probabilities do not account for the probability that the signal actually is $s_0(t)$ or $s_1(t)$
  - they are **conditional** ("if")

Computing conditional error probabilities

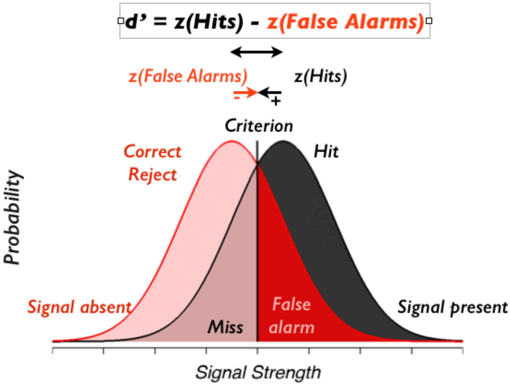

Figure 2: Conditional error probabilities

[image from hhttp://gru.stanford.edu/doku.php/tutorials/sdt]

Reminder: the Bayes rule

- Reminder: the Bayes rule

$$P(A \cap B) = P(B|A) \cdot P(A))$$

- Interpretation
  - The probability $P(A)$ is taken out from $P(B|A)$
  - $P(B|A)$ gives no information on $P(A)$, the chances of A actually happening
  - Example: $\mathrm{P(score} \mid \mathrm{shoot)} = \frac{1}{2}$. How many goals are scored?

Exercise

- A signal can have two possible values, 0 or 5. The signal 0 is affected by gaussian noise $\mathcal{N}(0, 0.5)$, while the signal 5 is affected by uniform noise $\mathcal{U}[-4, 4]$. The receiver performs ML decision based on a single sample.
  1. Compute the probability of a wrong decision when the original signal is $s_0(t)$
  2. Compute the probability of a wrong decision when the original signal is $s_1(t)$

Pitfalls of ML decision criterion

- The ML is based on comparing **conditional** probability density functions
  - conditioned by H_0 or by H_1
- Conditioning by H_0 and H_1 ignores the probability of H_0 or H_1 actually happening
  - We don't know how $p(H_0)$ or $P(H_1)$
- If $p(H_0) > p(H_1)$, we may want to move the threshold towards H_1, and vice-versa
  - because it is more likely that the signal is $s_0(t)$
  - and thus we want to "encourage" decision D_0

The minimum error probability criterion

- Takes into account the probabilities $P(H_0)$ and $P(H_1)$
- Goal is to **minimize the total probability of error** P_e
  - errors = false alarms and misses
- We need to find the decision regions R_0 and R_1

Probability of error

- Probability of false alarm

$$
\begin{aligned}
P(D_1 \cap H_0) =& P(D_1|H_0) \cdot P(H_0) \\
=& \int_{R_1} w(r|H_0)dx \cdot P(H_0) \\
=& (1 - \int_{R_0} w(r|H_0)dx \cdot P(H_0)
\end{aligned}
$$

- Probability of miss

$$
\begin{aligned}
P(D_0 \cap H_1) =& P(D_0|H_1) \cdot P(H_1) \\
=& \int_{R_0} w(r|H_1)dx \cdot P(H_1)
\end{aligned}
$$

- The sum is

$$P_e = P(H_0) + \int_{R_0} [w(r|H_1) \cdot P(H_1) - w(r|H_0) \cdot P(H_0)]dx$$

Minimum probability of error

- We want to minimize P_e, i.e. to minimize the integral
- To minimize the integral, we choose R_0 such that for all $r \in R_0$, the term inside the integral is **negative**
  - because integrating over all the interval where the function is negative ensures minimum value of integral
- So, when $w(r|H_1) \cdot P(H_1) - w(r|H_0) \cdot P(H_0) < 0$ we have $r \in R_0$, i.e. decision D_0
- Conversely, when $w(r|H_1) \cdot P(H_1) - w(r|H_0) \cdot P(H_0) > 0$ we have $r \in R_1$, i.e. decision D_1
- Therefore

$$w(r|H_1) \cdot P(H_1) - w(r|H_0) \cdot P(H_0) \underset{H_0}{\overset{H_1}{\gtrless}} 0$$

$$\frac{w(r|H_1)}{w(r|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \frac{P(H_0)}{P(H_1)}$$

Interpretation

- Similar to ML, but threshold depends on probabilities of the two hypotheses
  - When one hypotheses is more likely than the other, the threshold is pushed in its favor, towards the other
- Also based on a **likelihood ratio** test, just like ML

Minimum probability of error - gaussian noise

- Assuming the noise is gaussian (normal), $\mathcal{N}(0, \sigma^2)$

$$w(r|H_1) = e^{-\frac{(r-A)^2}{2\sigma^2}}$$

$$w(r|H_0) = e^{-\frac{r^2}{2\sigma^2}}$$

- Apply natural logarithm

$$-\frac{(r-A)^2}{2\sigma^2} + \frac{r^2}{2\sigma^2} \underset{H_0}{\overset{H_1}{\gtrless}} \ln\left(\frac{P(H_0)}{P(H_1)}\right)$$

- Equivalently

$$2rA - A^2 \underset{H_0}{\overset{H_1}{\gtrless}} 2\sigma^2 \cdot \ln\left(\frac{P(H_0)}{P(H_1)}\right)$$

$$r \underset{H_0}{\overset{H_1}{\gtrless}} \underbrace{\frac{A^2 + 2\sigma^2 \cdot \ln\left(\frac{P(H_0)}{P(H_1)}\right)}{2A}}_{T}$$

Decision regions

- We still compare with a threshold T, but its value is shifted towards the less probable hypothesis
  - T depends on the ratio $\frac{P(H_0)}{P(H_1)}$
- Decision regions
  - $R_0 = (-\infty, T]$
  - $R_1 = [T, \infty)$
  - will be different for other noise distributions (non-gaussian)

Exercises

- An information source provides two messages with probabilities $p(a_0) = \frac{2}{3}$ and $p(a_1) = \frac{1}{3}$. The messages are encoded as constant signals with values -5 (a_0) and 5 (a_1). The signals are affected by gaussian noise $\mathcal{N}(0, \sigma^2 = 1)$ The receiver takes one sample r. Decision is done by comparing r with a threshold value T, as follows: if $r < T$ it is decided that the transmitted message is a_0, otherwise it is a_1.
  1. Find the threshold value T according to the minimum probability of error criterion
  2. What if the signal 5 is affected by uniform noise $\mathcal{U}[-4, 4]$?
  3. What are the probabilities of false alarm and of miss?

Minimum risk (cost) criterion

- What if we care more about one type of errors (e.g. false alarms) than other kind (e.g. miss)?
- Minimum risk (cost) criterion: assign costs to decisions, minimize average cost
  - C_{ij} = cost of decision D_i when true hypothesis was H_j
  - C_{00} = cost for good detection D_0 in case of H_0
  - C_{10} = cost for false alarm (detection D_1 in case of H_0)
  - C_{01} = cost for miss (detection D_0 in case of H_1)
  - C_{11} = cost for good detection D_1 in case of H_1
- The risk = the average cost

$$R = C_{00}P(D_0 \cap H_0) + C_{10}P(D_1 \cap H_0) + C_{01}P(D_0 \cap H_1) + C_{11}P(D_1 \cap H_1)$$

- Minimum risk criterion: **minimize the risk R**

Computations

- Proof on table:
  - Use Bayes rule
  - Notations: $w(r|H_j)$ (*likelihood*)
  - Probabilities: $\int_{R_i} w(r|H_j)dV$
- Conclusion, **decision rule is**

$$\frac{w(r|H_1)}{w(r|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \frac{(C_{10} - C_{00})p(H_0)}{(C_{01} - C_{11})p(H_1)}$$

Interpretation

- Similar to ML and to minimum probability of error criteria
  - also uses a **likelihood ratio** test
- Both probabilities and the assigned costs can move threshold towards one side or the other
- If $C_{10} - C_{00} = C_{01} - C_{11}$, reduces to previous criterion (minimum probability of error)
  - e.g. if $C_{00} = C_{11} = 0$, and $C_{10} = C_{01}$

In gaussian noise

- If the noise is gaussian (normal), then similar to other criteria, apply logarithm
- Equivalently

$$-(r-A)^2 + r^2 \underset{H_0}{\overset{H_1}{\gtrless}} \underbrace{2\sigma^2 \cdot \ln\left(\frac{(C_{10}-C_{00})p(H_0)}{(C_{01}-C_{11})p(H_1)}\right)}_{C}$$

$$r \underset{H_0}{\overset{H_1}{\gtrless}} \underbrace{\frac{A^2 + 2\sigma^2 \cdot \ln\left(\frac{(C_{10}-C_{00})p(H_0)}{(C_{01}-C_{11})p(H_1)}\right)}{2A}}_{T}$$

Example

- Example at blackboard: 0 / 5, random noise with $N(0, \sigma^2)$, one sample

Neymar-Pearson criterion

- Neymar-Pearson criterion: maximize probability of a hit ($P(D_1 \cap H_1)$) while keeping probability of false alarms smaller then a limit ($P(D_1 \cap H_0) \leq \lambda$)
- Deduce the threshold T from the limit condition $P(D_1 \cap H_0) = \lambda$

Exercise

- An information source provides two messages with probabilities $p(a_0) = \frac{2}{3}$ and $p(a_1) = \frac{1}{3}$.
- The messages are encoded as constant signals with values -5 (a_0) and 5 (a_1).
- The signals are affected by noise with triangular distribution $[-5, 5]$.
- The receiver takes one sample r.
- Decision is done by comparing r with a threshold value T, as follows: if $r < T$ it is decided that the transmitted message is a_0, otherwise it is a_1.

1. Find the threshold value T according to the Neymar-Pearson criterion, considering $P_{fa} \leq 10^{-2}$
2. What is the probability of hit?

Two non-zero levels

- What if the s_0 signal is not 0, but another constant signal $s_0 = B$?
- Noise distribution $w(r|H_0)$ is centered on B, not 0
- Otherwise, everything else stays the same
- Performance is defined by the gap between the two levels $(A - B)$
  - same performance if $s_0 = 0$, $s_1 = A$ or if $s_0 = -\frac{A}{2}$ and $s_1 = \frac{A}{2}$
- Valid for all decision criteria

Differential vs single-ended signalling

- Single-ended signaling: one signal is 0, other is non-zero
  - $s_0 = 0$, $s_1 = A$
- Differential signaling: use two non-zero levels with different sign, same absolute value
  - $s_0 = -\frac{A}{2}$, $s_1 = \frac{A}{2}$
- Which is better?

Differential vs single-ended signalling

- If gap difference between levels is the same, performance is the same
- Average power of a signal = average squared value
- For differential signal: $P = \left(\pm\frac{A}{2}\right)^2 = \frac{A^2}{4}$
- For signal ended signal: $P = P(H_0) \cdot 0 + P(H_1)\,(A)^2 = \frac{A^2}{2}$
    - assuming equal probabilities $P(H_0) = P(H_1) = \frac{1}{2}$
- Differential uses half the power of single-ended (i.e. better)

Summary of criteria

- We have seen decision based on 1 sample r, between 2 constant levels
- All decisions are based on a likelihood-ratio test

$$\frac{w(r|H_1)}{w(r|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} K$$

- Different criteria differ in the chosen value of K (likelihood threshold)
- Depending on the noise distributions, the real axis is partitioned into regions
  - region R_0: if r is in here, decide D_0
  - region R_1: if r is in here, decide D_1
  - e.g. $R_0 = (-\infty, \frac{A+B}{2}]$, $R_1 = (\frac{A+B}{2}, \infty)$ (ML)

Receiver Operating Characteristic

- The receiver performance is usually represented with **"Receiver Operating Characteristic" (ROC)** graph
- It is a graph of hit probability $P_d = P(D_1 \cap H_1)$ (correct detection) as a function of false alarm probability $P_{fa} = P(D_1 \cap H_0)$

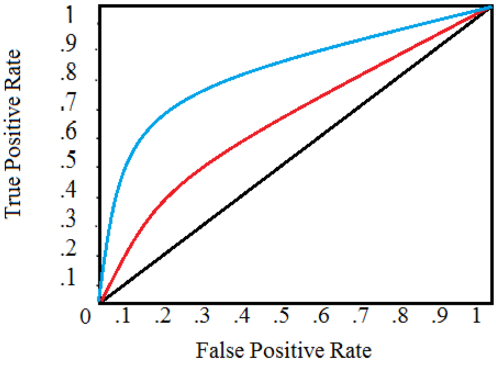

Figure 3: Sample ROC curves

Receiver Operating Characteristic

- There is always a **tradeoff** between good P_d and bad P_{fa}
  - to increase P_d one must also increase P_{fa}
  - if we want to make sure we don't miss any real detections (increase P_d), we pay by increasing the chances of false alarms
- Different criteria = different likelihood thresholds K = different points on the graph = different tradeoffs
  - but the tradeoff cannot be avoided
- How to improve the receiver?
  - i.e. increase P_D while keeping P_{fa} the same

Performance of likelihood-ratio decoding in WGN

- WGN = "White Gaussian Noise"
- Assume equal probabilities $P(H_0) = P(H_1) = \frac{1}{2}$
- All decisions are based on a likelihood-ratio test

$$\frac{w(r|H_1)}{w(r|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} K$$

- Hit probability is

$$\begin{aligned}
P_{hit} =& P(D_1|H_1)P(H_1) \\
=& P(H_1)\int_T^{\infty} w(r|H_1) \\
=& P(H_1)(F(\infty) - F(T)) \\
=& \frac{1}{4}\left(1 - erf\left(\frac{T-A}{\sqrt{2}\sigma}\right)\right) \\
=& Q\left(\frac{T-A}{\sqrt{2}\sigma}\right)
\end{aligned}$$

Performance of likelihood-ratio decoding in WGN

- False alarm probability is

$$
\begin{aligned}
P_{fa} =& P(D_1|H_0)P(H_0) \\
=& P(H_0)\int_T^{\infty} w(r|H_0) \\
=& P(H_0)(F(\infty) - F(T)) \\
=& \frac{1}{4}\left(1 - erf\left(\frac{T-0}{\sqrt{2}\sigma}\right)\right) \\
=& Q\left(\frac{T}{\sqrt{2}\sigma}\right)
\end{aligned}
$$

- Therefore $\frac{T}{\sqrt{2}\sigma} = Q^{-1}\left(P_{fa}\right)$
- Replacing in P_{hit} yields

$$
P_{hit} = Q\left(\underbrace{Q^{-1}\left(P_{fa}\right)}_{constant} - \frac{A}{\sqrt{2}\sigma}\right)
$$

Signal-to-noise ratio

- **Signal-to-noise ratio (SNR)** $= \frac{\text{power of original signal}}{\text{power of noise}}$
- Average power of a signal $=$ average squared value $= \overline{X^2}$
  - Original signal power is $\frac{A^2}{2}$
  - Noise power is $\overline{X^2} = \sigma^2$ (when noise mean value $\mu = 0$)
- In our case, SNR $= \frac{A^2}{2\sigma^2}$

$$P_{hit} = Q\left(\underbrace{Q^{-1}\left(P_{fa}\right)}_{constant} - \sqrt{SNR}\right)$$

- For a fixed P_{fa}, P_{hit} increases with SNR
  - Q is a monotonic decreasing function

Performance depends on SNR

- Receiver performance increases with SNR increase
  - high SNR: good performance
  - poor SNR: bad perfomance

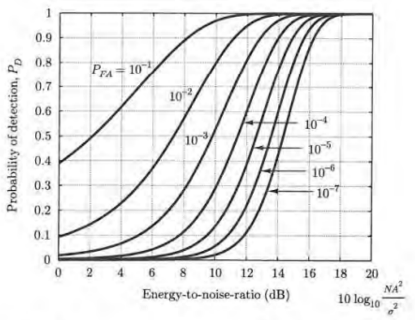

Figure 4: Detection performance depends on SNR

[source: Fundamentals of Statistical Signal Processing, Steven Kay]

Decision between hypotheses

- Statistical decision is not useful merely for detecting signals
- We are in fact deciding between two different probability distributions
  - regardless of what the two distributions mean
- For detection of constant signals, we choose between two distributions with **different average value**, generally
  - one distribution has average value 0, the other one A
- But we can choose between distributions that differ in other parameters
  - average value, or
  - variance, or
  - shape, etc

Decision between hypotheses

- Example: We have a sample with value $r = 2.5$. It can come from a distribution $\mathcal{N}(0, \sigma^2 = 1)$ (hypothesis H_0) or from $\mathcal{N}(0, \sigma^2 = 2)$ (hypothesis H_1). Which hypothesis do we think is true?
  - It is the variance that differs, not the average value
- We can use the exact same criteria as before
  - Draw the two distributions
  - Compute the likelihoods $w(r|H_0)$ and $w(r|H_1)$ for r
  - Decide based on likelihood ratio using some criterion

II.3 Detection of constant signals with multiple samples

Multiple samples from a constant signal

- Suppose we have multiple samples, not just 1
- The samples are arranged in a **sample vector**

$$\mathbf{r} = [r_1, r_2, ... r_N]$$

- In each hypotheses, the signal is a **random process**
  - H_0: random process with average value 0
  - H_1: random process with average value A
- Assuming the noise is stationary and ergodic, the signal random process is stationary and ergodic (signal = constant + noise)
- The values of $\mathbf{r}$ are described by the **distribution of order** N of the random processes, $w_N(\mathbf{r}) = w_N(r_1, r_2, ... r_N)$
- Assuming the noise is white noise, the sample times don't matter

Likelihood-based of vector samples

- We can apply **the same criteria** based on likelihood ratio as for 1 sample

$$\frac{w_N(\mathbf{r}|H_0)}{w_N(\mathbf{r}|H_1)} \underset{H_0}{\overset{H_1}{\gtrless}} K$$

- Notes
  - $\mathbf{r}$ is a vector; we consider the likelihood of all the samples
  - the hypotheses H_0 and H_1 are the same as for 1 sample
  - $w_N(\mathbf{r}|H_0) =$ likelihood of the whole vector $\mathbf{r}$ being obtained in hypothesis H_0
  - $w_N(\mathbf{r}|H_1) =$ likelihood of the whole vector $\mathbf{r}$ being obtained in hypothesis H_1
  - the value of K is given by the actual decision criterion used
- Interpretation: we choose the hypothesis that is most likely to have produced the observed data
  - the same, but now the data = multiple samples

Separation

- Assuming the noise is white noise, the samples r_i are **multiple independent realizations of the same distribution**
- In that case the joint distributions $w_N(\mathbf{r}|H_j)$ can be decomposed as a product

$$w_N(\mathbf{r}|H_j) = w(r_1|H_j) \cdot w(r_2|H_j) \cdot ... \cdot w(r_N|H_j)$$

- The $w(r_i|H_j)$ are just the likelihoods of each individual sample
  - e.g. the likelihood of obtaining $[5.1, 4.7, 4.9]$ = likelihood of obtaining 5.1 $\times$ likelihood of getting 4.7 $\times$ likelihood of getting 4.9

Separation

- Then all likelihood ratio criteria can be written as

$$\frac{w_N(\mathbf{r}|H_1)}{w_N(\mathbf{r}|H_0)} = \frac{w(r_1|H_1)}{w(r_1|H_0)} \cdot \frac{w(r_2|H_1)}{w(r_2|H_0)} \dots \frac{w(r_N|H_1)}{w(r_N|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} K$$

- The likelihood ratio of a vector of samples = product of likelihood ratio for each sample

Particular case: AWGN

- AWGN = "Additive White Gaussian Noise"
- In hypothesis H_1: $w(r_i|H_1) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(r_i - A)^2}{2\sigma^2}}$
- In hypothesis H_0: $w(r_i|H_1) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{r_i^2}{2\sigma^2}}$
- Likelihood ratio for vector $\mathbf{r}$

$$\frac{w_N(\mathbf{r}|H_1)}{w_N(\mathbf{r}|H_0)} = \frac{e^{-\frac{\sum (r_i - A)^2}{2\sigma^2}}}{e^{-\frac{\sum (r_i)^2}{2\sigma^2}}}$$

- We can interpret this likelihood ratio in two ways

Interpretation 1: average value of samples

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$$
\begin{aligned}
\frac{w_N(\mathbf{r}|H_1)}{w_N(\mathbf{r}|H_0)} &= \frac{e^{-\frac{\sum (r_i - A)^2}{2\sigma^2}}}{e^{-\frac{\sum (r_i)^2}{2\sigma^2}}} \\
&= e^{-\frac{\sum (r_i - A)^2 - \sum (r_i)^2}{2\sigma^2}} \\
&= e^{-\frac{\sum (r_i^2 - 2r_i A + A^2) - \sum (r_i)^2}{2\sigma^2}} \\
&= e^{-\frac{\sum (-2r_i A + A^2)}{2\sigma^2}} \\
&= e^{-\frac{-2A \sum (r_i) + NA^2}{2\sigma^2}} \\
&= e^{-\frac{-2A \frac{\sum (r_i)}{N} + A^2}{2\frac{\sigma^2}{N}}}
\end{aligned}
$$