Discrete Bayes

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Outline

1. The Basic Perspective
2. The Decision Rule
3. Maximizing Expected Gain: Bayes Decision Rule
The Basic Perspective
The Decision Rule
Maximizing Expected Gain: Bayes Decision Rule

Perspective
Consider the task of recognizing a truck with a machine gun mounted on its back end in the context of guerilla urban warfare. The sensor is a camera. The unit of observation is the pixel, millions of them. No one pixel of the truck carries sufficient information about the class.
Grouping

The units of observation have to be grouped into relevant groups. Classification must be based on features extracted from the relevant groups.
The units of observations are transaction records. For example the records might be records of the secure log. The problem is to decide whether or not an IP address should be banned.

Aug 16 04:41:06 cunygrid sshd[12535]:
    Invalid user alexis from 221.130.78.253
Aug 16 04:41:06 cunygrid sshd[12543]:
    input_userauth_request: invalid user alexis
Aug 16 04:41:06 cunygrid sshd[12535]:
    pam_unix(sshd:auth): check pass; user unknown
Aug 16 04:41:06 cunygrid sshd[12535]:
    pam_unix(sshd:auth): authentication failure;
    logname= uid=0 euid=0 tty=ssh
    ruser= rhost=221.130.78.253
Cyber Attack Units of Observation

- Each observation is a record
- A record is a set of attribute value pairs

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date</td>
<td></td>
</tr>
<tr>
<td>Time</td>
<td></td>
</tr>
<tr>
<td>Connection ID</td>
<td></td>
</tr>
<tr>
<td>Login ID</td>
<td></td>
</tr>
<tr>
<td>IP address</td>
<td></td>
</tr>
<tr>
<td>Login Id accepted/rejected</td>
<td></td>
</tr>
<tr>
<td>Password</td>
<td></td>
</tr>
<tr>
<td>Password accepted/rejected</td>
<td></td>
</tr>
<tr>
<td>Disconnection</td>
<td></td>
</tr>
</tbody>
</table>
Grouping Units of Observation

- Thread by connection id
- Thread by login ID
- Thread by IP address
- Thread by Time interval
Extracting Features

For a set of records in the given time interval with same IP address:

- Number of records
- Number of login ID records
- Number of login ID’s accepted
- Number of disconnects
Extracting Features

For a set of records in the given time interval with same IP address and login ID:

- Number of records
- Number of passwords attempted
- Number of passwords accepted
- Number of disconnects
Grouping and Feature Extracting

The process of grouping together the raw observation units to the unit of observation in the machine learning process and the process of defining the feature vector for the grouped units is part of the art of Machine Learning.
Be Rational, Use Expected Value

When faced with a number of actions, each of which could give rise to more than one possible outcome with different probabilities, the rational action is to:

- Identify all possible outcomes
- Determine their values, utilities, (positive or negative)
- Determine the probabilities that will result from each course of action
- Multiply the two to give an expected value
- The best action is the one that gives rise to the highest expected value

(Blaise Pascal, Pensées, 1670)
**Highest Expected Value**

- $a_1, a_2$ Two possible actions
- $e_1, e_2, e_3$ Three possible economic gains
- The Probabilities for three gains under action $a_1$
  - $P(e_1|a_1), P(e_2|a_1), P(e_3|a_1)$
- The Probabilities for three gains under action $a_2$
  - $P(e_1|a_2), P(e_2|a_2), P(e_3|a_2)$

| Action | Probabilities $P(e|a)$ | Expected Value |
|--------|------------------------|----------------|
| $a_1$  | $e_1 = 1$ $e_2 = 3$ $e_3 = 0$ | $0.25 \times 1 + 0.5 \times 3 + 0.25 \times 0 = 1.75$ |
| $a_2$  | $e_1 = 1$ $e_2 = 3$ $e_3 = 0$ | $0.5 \times 1 + 0.2 \times 3 + 0.3 \times 0 = 1.1$ |

Choose Action $a_1$
Bayes Theorem

- $c$: Class
- $d$: Observed data
- $P(d | c)$: The class conditional probabilities

Current state of knowledge $P(c)$. New evidence, the observed data $d$. What is the updated probability of $c$: $P(c | d)$?

- $P(c | d) = \frac{P(c, d)}{P(d)}$
- $P(d | c) = \frac{P(c, d)}{P(c)}$
- $P(c | d) = \frac{P(d | c)P(c)}{P(d)}$

Thomas Bayes (1701-1761), first showed how to use new evidence to update beliefs.
In what follows, the unit being observed is assumed to be that which arises from the grouping process. The measurement is assumed to be the feature vector.
In the pattern discrimination or pattern identification process, a unit is observed or measured and a category assignment is made on the basis of the measurement. This event can be characterized by its three parts:

- unit has true category identification $c^j$, a member of the set $C$
- decision rule assignment is to category $c^k$, a member of the set $C$
- measurement $d$ is made from the set $D$
unit has true category identification $c^j$, a member of the set $C$

decision rule assignment is to category $c^k$, a member of the set $C$

measurement $d$ is made from the set $D$

Denote this event by $(c^j, c^k, d)$ It has a probability of occurring:

$$P(True = c^j, Assigned = c^k, Meas = d)$$
Economic Consequences

The act of making the assignment carries consequences, economically or in terms of utility.

Assumption

These consequences depend only on which category is the true category identification for the unit and which category is the assigned category identification for the unit. They do not depend on which particular unit is being assigned or on what measurement values the unit to be assigned has.
The Economic Gain Matrix is Application Dependent
### Confusion Matrix

The Confusion Matrix Tells How Correct Is the Machine Learning

<table>
<thead>
<tr>
<th></th>
<th>$c^1$</th>
<th>$c^2$</th>
<th>...</th>
<th>$c^K$</th>
<th>...</th>
<th>$c^K$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c^1$</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>$c^2$</td>
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<td>...</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>$c^K$</td>
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<td></td>
<td></td>
</tr>
</tbody>
</table>

The Confusion Matrix is a table that shows how well a machine learning model predicts the true class labels. Each cell in the table represents the probability of assigning a prediction to a class given the true class. For example, $P_{TA}(c^j, c^k)$ is the probability of assigning class $c^j$ when the true class is $c^k$. The diagonal cells represent correct predictions, while the off-diagonal cells represent errors. The overall performance of the model can be assessed by examining the confusion matrix and calculating metrics such as accuracy, precision, recall, and F1 score.
The probability of correct identification, $P_c$, is the probability that the True Identification equals the Assigned Identification. It is defined by

$$P_c = \sum_{j=1}^{K} P_{TA}(c^j, c^j)$$

the sum of the diagonal entries of the confusion matrix.
What is the probability of observing a unit whose true class identification is $c^j$ and whose assigned class identification is $c^k$?

$$P_{TA}(c^j, c^k) = \sum_{d \in D} P_{TA}(c^j, c^k, d)$$
Expected Economic Gain

For each true-assigned category identification pair \((c^j, c^k)\) we know its

\[
\text{economic gain} \quad e(c^j, c^k)
\]

and probability \(P_{TA}(c^j, c^k)\).
How do we compute the average or expected value of the consequence?

\[
E[e] = \sum_{j=1}^{K} \sum_{k=1}^{K} e(c_j, c_k) P_{TA}(c_j, c_k)
\]

\[
= \sum_{j=1}^{K} \sum_{k=1}^{K} e(c_j, c_k) \sum_{d \in D} P_{TA}(c_j, c_k, d)
\]
### Expected Gain

#### Confusion Matrix

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<th>$c^1$</th>
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<th>$c^K$</th>
</tr>
</thead>
<tbody>
<tr>
<td>TRUE</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$c^K$</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$P_{TA}(c^j, c^k)$

#### Economic Gain Matrix

<table>
<thead>
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<th>$c^K$</th>
</tr>
</thead>
<tbody>
<tr>
<td>TRUE</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$c^K$</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$e(c^j, c^k)$

#### Expected Gain

$$E[e] = \sum_{j=1}^{K} \sum_{k=1}^{K} e(c^j, c^k) P_{TA}(c^j, c^k)$$
What are the processes which lead to the event \((c^j, c^k, d)\) occurring?

1. There is a unit having measurement \(d\) whose true class identification is \(c^j\).

2. Using only the measurement \(d\), the decision rule makes the assignment to class \(c^k\).
Nature and the Decision Rule are not in collusion

In making the class assignment, the decision rule must only use the measurement data. The decision rule cannot use the true class identification.

- nature only uses $d$ in deciding true class identification $c^j$
- decision rule only uses $d$ in deciding the assigned class identification $c^k$
Fair Game Assumption

$c^k$ assigned class
$c^j$ true class
d measurement data

\( P_{AT}(c^k \mid (c^j, d)) = P_A(c^k \mid d) \)

Therefore,

\[
P_{AT}(c^k, c^j \mid d) = \frac{P_{AT}(c^k, c^j, d)}{P(d)}
\]

\[
= \frac{P_{AT}(c^k \mid c^j, d)P_T(c^j, d)}{P(d)}
\]

\[
= P_A(c^k \mid d)P_T(c^j \mid d)
\]
Nature and the decision rule are not in collusion. Given that a unit has measurements, $d$, the assigned class which the decision rule determines and the true class which nature determines are statistically independent.

$$P_{AT}(c^k, c^i \mid d) = P_A(c^k \mid d)P_T(c^i \mid d)$$
Let $f_d(c^k)$ be the conditional probability that the decision rule assigns a unit to class $c^k$ given that the unit has measurement $d$. We call $f$ the decision rule.
Since, conditioned on measurement $d$, the true and assigned class are statistically independent,

$$P_{TA}(c^j, c^k | d) = P_T(c^j | d)f_d(c^k)$$
By definition of conditional probability,

$$P_{TA}(c^j, c^k | d) = \frac{P_{TA}(c^j, c^k, d)}{P(d)}$$

$$P_{TA}(c^j, c^k, d) = P_{TA}(c^j, c^k | d)P(d)$$
The Probabilistic Decision Rule

\[ P_{TA}(c^i, c^k, d) = P_{TA}(c^i, c^k | d)P(d) \]
\[ = P_T(c^i | d)f_d(c^k)P(d) \]
\[ = P_T(c^i, d)f_d(c^k) \]
The Expected Gain is then

\[
E[e; f] = \sum_{j=1}^{K} \sum_{k=1}^{K} e(c^j, c^k) \sum_{d \in D} P_{TA}(c^j, c^k, d)
\]

\[
= \sum_{j=1}^{K} \sum_{k=1}^{K} e(c^j, c^k) \sum_{d \in D} P_T(c^j, d) f_d(c^k)
\]

\[
= \sum_{d \in D} \sum_{k=1}^{K} f_d(c^k) \left[ \sum_{j=1}^{K} e(c^j, c^k) P_T(c^j, d) \right]
\]
Maximizing

\[ a_1, \ldots, a_L \text{ is a sequence of } L \text{ numbers} \]

\[ p_1, \ldots, p_L \text{ is a sequence of unknown numbers satisfying} \]

\[ p_i \geq 0 \]

\[ \sum_{i=1}^{L} p_i = 1 \]

Find an upper bound for \[ \sum_{i=1}^{L} a_i p_i \] over all possible such sequences \[ p_1, \ldots, p_L \] satisfying the constraints.
Maximizing

\[ a_i \leq \max_j a_j \text{ for } i = 1, \ldots, L \]

Since \( p_i \geq 0 \),

\[ a_i p_i \leq \left[ \max_j a_j \right] p_i \]
Maximizing Expected Gain: Bayes Decision Rule

Since inequality holds for each $i$, it must also hold for the sum.

$$
\sum_{i=1}^{L} a_i p_i \leq \sum_{i=1}^{L} \left[ \max_{j=1,\ldots,L} a_j \right] p_i
$$

$$
\leq \left[ \max_{j=1,\ldots,L} a_j \right] \sum_{i=1}^{L} p_i
$$

$$
\leq \left[ \max_{j=1,\ldots,L} a_j \right]
$$
Maximizing

If $p_1, \ldots, p_L$ is a sequence of $L$ numbers satisfying

$$p_i \geq 0 \text{ and } \sum_{i=1}^{L} p_i = 1$$

then

$$\max_{j=1,\ldots,L} a_j \quad \geq \quad \sum_{i=1}^{L} a_i p_i$$

Thus,

$$\max_{j=1,\ldots,L} a_j \quad \text{is an upper bound for} \quad \sum_{i=1}^{L} a_i p_i$$
Maximizing

Is this upper bound, \( \max_{j=1,\ldots,L} a_j \) for \( \sum_{i=1}^L a_i p_i \)
the lowest possible upper bound?

Yes, since it is achievable by appropriate choice of \( p_i \)’s.

Set \( p_i = 0 \) if \( a_i < \max_{j=1,\ldots,L} a_j \).

Set remaining \( p_i \)’s so that \( 0 \leq p_i \) and \( \sum_{i=1}^L p_i = 1 \).
Suppose $a_{ij}$, $i = 1, 2, \ldots, L$ and $j = 1, 2, \ldots, J$ is a sequence of numbers and $p_{ij}$ satisfies

$$0 \leq p_{ij} \text{ and } \sum_{j=1}^{J} p_{ij} = 1 \text{ for } i = 1, 2, \ldots, L.$$ 

Then the lowest upper bound for $\sum_{j=1}^{J} a_{ij} p_{ij}$ is $\max_{k=1,\ldots,K} a_{ik}$, $i = 1, 2, \ldots, L$. 
Maximizing

\[ a_{ij} \leq \max_k a_{ik} \text{ for each } i \text{ and } j. \text{ Since } p_{ij} \geq 0. \]

\[ p_{ij} a_{ij} \leq p_{ij} \max_k a_{ik} \text{ for each } i \text{ and } j. \text{ Summing over } j, \]

\[ \sum_{j=1}^{J} p_{ij} a_{ij} \leq \sum_{j=1}^{J} p_{ij} \max_k a_{ik} = \max_k a_{ik} \sum_{j=1}^{J} p_{ij} \]

\[ \leq \max_k a_{ik}. \]

Thus, \( \max_k a_{ik} \) is an upper bound for \( \sum_{j=1}^{J} p_{ij} a_{ij} \).
Maximizing Expected Gain: Bayes Decision Rule

\[
\max_k a_{ik} \text{ is the lowest upper bound for } \sum_{j=1}^{J} p_{ij} a_{ij} \text{ since it is achievable.}
\]

Set \( p_{ij} = 0 \) if \( a_{ij} \leq \max_k a_{ik} \)

Set remaining \( p_{ij} \)'s so that

\[ 0 \leq p_{ij} \text{ and } \sum_{j=1}^{J} p_{ij} = 1. \]
The Expected Gain is then

\[
E[e; f] = \sum_{j=1}^{K} \sum_{k=1}^{K} e(c_j, c_k) \sum_{d \in D} P_T(c_j, c_k, d)
\]

\[
= \sum_{j=1}^{K} \sum_{k=1}^{K} e(c_j, c_k) \sum_{d \in D} P_T(c_j, d)f_d(c_k)
\]

\[
= \sum_{d \in D} f_d(c_k) \left[ \sum_{j=1}^{K} e(c_j, c_k) P_T(c_j, d) \right]
\]
Maximizing Expected Gain

But for any conditional probability $f_d(c)$,

$$\sum_{d \in D} \left\{ \sum_{k=1}^{K} f_d(c^k) \left[ \sum_{j=1}^{K} e(c^j, c^k) P_T(c^j, d) \right] \right\} \leq \sum_{d \in D} \left\{ \max_n \left[ \sum_{j=1}^{K} e(c^j, c^n) P_T(c^j, d) \right] \right\}$$
Maximizing Expected Gain

If for each $d$, there exists a unique $m = m(d)$ such that

$$
\sum_{j=1}^{K} e(c^j, c^k) P_T(c^j, d) \leq \sum_{j=1}^{K} e(c^j, c^m) P_T(c^j, d), \text{ for each } k,
$$

Then setting

$$
\begin{align*}
    f_d(c^m) &= 1 \\
    f_d(c^k) &= 0, \quad k \neq m
\end{align*}
$$

achieves the upper bound.
Maximizing Expected Gain

In general, the upper bound is achievable by using a decision rule $f$ defined by $f_d(c^k) = 0$ for each $c^k$ and $d$ such that

$$\sum_{j=1}^{K} e(c^j, c^k) P_T(c^j, d) < \max_n \sum_{j=1}^{K} e(c^j, c^n) P_T(c^j, d)$$

and the remaining $f_d(c^k)$ are set in any way so that

$$f_d(c^k) \geq 0$$

$$\sum_{k=1}^{K} f_d(c^k) = 1$$
A decision rule $f$ is called a Bayes decision rule if and only if $E[e; f] \geq E[e; g]$ for any decision rule $g$. 
A Bayes rule can always be implemented as a deterministic decision rule.

\[
\sum_{j=1}^{K} e(c_j, c^K) P_T(c_j, d)
\]
Bayes Decision Rule

Given measurement $d$, assign to any class $c^k$ satisfying

$$\sum_{j=1}^{K} e(c^j, c^k)P_T(c^j, d) \geq \sum_{j=1}^{K} e(c^j, c^n)P_T(c^j, d), n = 1, \ldots, K$$

If the economic gain matrix $e$ is the identity, then assign to any class $c^k$ satisfying

$$P_T(c^k, d) \geq P_T(c^n, d), n = 1, \ldots, K$$

$$E[e] = \sum_{d \in D} \max_{n=1,\ldots,K} P_T(c^n, d) = P_{\text{correct}}$$
Bayes Decision Rule

<table>
<thead>
<tr>
<th>$P_T(c, d)$</th>
<th>Measurement</th>
<th>$e$</th>
<th>Assigned</th>
</tr>
</thead>
<tbody>
<tr>
<td>True</td>
<td>$d^1$</td>
<td>$d^2$</td>
<td>$d^3$</td>
</tr>
<tr>
<td>$c^1$</td>
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<td>.18</td>
<td>.3</td>
</tr>
<tr>
<td>$c^2$</td>
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<td>.04</td>
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<table>
<thead>
<tr>
<th>$f_d(c)$</th>
<th>Measurement</th>
</tr>
</thead>
<tbody>
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</tr>
<tr>
<td>$c^1$</td>
<td>0</td>
</tr>
<tr>
<td>$c^2$</td>
<td>1</td>
</tr>
</tbody>
</table>

$E[e] = .2 \times 2 + .16 \times 2 + .3 \times 1 = 1.02$
The Basic Perspective
The Decision Rule
Maximizing Expected Gain: Bayes Decision Rule

The Confusion Matrix

\[ P_{TA}(c^1, c^1) = \sum_{d \in D} f_d(c^1)P_T(c^1, d) \]
\[ P_{TA}(c^1, c^2) = \sum_{d \in D} f_d(c^2)P_T(c^1, d) \]
\[ P_{TA}(c^2, c^1) = \sum_{d \in D} f_d(c^1)P_T(c^2, d) \]
\[ P_{TA}(c^2, c^2) = \sum_{d \in D} f_d(c^2)P_T(c^2, d) \]

<table>
<thead>
<tr>
<th>( P_{TA} )</th>
<th>Assigned</th>
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</thead>
<tbody>
<tr>
<td>True</td>
<td>( c^1 )</td>
</tr>
<tr>
<td>( c^1 )</td>
<td>( P_{TA}(c^1, c^1) )</td>
</tr>
<tr>
<td>( c^2 )</td>
<td>( P_{TA}(c^2, c^1) )</td>
</tr>
</tbody>
</table>
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The Confusion Matrix

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<td>$f_d$</td>
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<table>
<thead>
<tr>
<th>$P_{TA}$</th>
<th>Assigned</th>
<th>$P_T$</th>
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</thead>
<tbody>
<tr>
<td>True</td>
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<td>$c^2$</td>
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<tr>
<td>$c^1$</td>
<td>.3</td>
<td>.3</td>
</tr>
<tr>
<td>$c^2$</td>
<td>.04</td>
<td>.36</td>
</tr>
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</table>
### The Confusion Matrix

The Confusion Matrix is a table that shows the relationship between true labels and predicted labels. It is used in machine learning to evaluate the performance of classification models.

<table>
<thead>
<tr>
<th>( P_T(c, d) )</th>
<th>Measurement</th>
<th>( P_{TA} )</th>
<th>Assigned</th>
<th>( P_T )</th>
</tr>
</thead>
<tbody>
<tr>
<td>True</td>
<td>( d^1 )</td>
<td>( d^2 )</td>
<td>( d^3 )</td>
<td>( c^1 )</td>
</tr>
<tr>
<td>( c^1 )</td>
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<td>.18</td>
<td>.3</td>
<td>( .48 )</td>
</tr>
<tr>
<td>( c^2 )</td>
<td>.2</td>
<td>.16</td>
<td>.04</td>
<td>( .2 )</td>
</tr>
<tr>
<td>( f_d )</td>
<td>( c^2 )</td>
<td>( c^1 )</td>
<td>( c^1 )</td>
<td>( .2 )</td>
</tr>
</tbody>
</table>
Given measurement \( d \), assign to any class \( c^k \) satisfying

\[
\sum_{j=1}^{K} e(c^j, c^k) P_T(c^j, d) \geq \sum_{j=1}^{K} e(c^j, c^n) P_T(c^j, d), n = 1, \ldots, K
\]

Or equivalently, assign to any class \( c^k \) satisfying

\[
\sum_{j=1}^{K} e(c^j, c^k) \frac{P_T(c^j, d)}{P(d)} \geq \sum_{j=1}^{K} e(c^j, c^n) \frac{P_T(c^j, d)}{P(d)}, n = 1, \ldots, K
\]
Bayes Decision Rule

Given measurement $d$, assign to any class $c^k$ satisfying

$$\sum_{j=1}^{K} e(c^j, c^k) P_T(c^j|d) \geq \sum_{j=1}^{K} e(c^j, c^n) P_T(c^j|d), \quad n = 1, \ldots, K$$

Therefore, the only probability information we need for a Bayes rule are the conditional probabilities

$$P_T(c^j|d), \quad j = 1, \ldots, K$$
Two Class Bayes Rule

Assume the economic gain for a correct assignment is greater than the gain for an incorrect assignment.

\[
e(c^1, c^1) > e(c^1, c^2) \\
e(c^2, c^2) > e(c^2, c^1)
\]

Assume all probabilities are positive
Assign to class \(c^1\) if
\[
P(c^1|d)e(c^1, c^1) + P(c^2|d)e(c^2, c^1) \geq P(c^1|d)e(c^1, c^2) + P(c^2|d)e(c^2, c^2)
\]
Otherwise assign to class \(c^2\).

This inequality can be simplified.

\[
\frac{P(c^1|d)(e(c^1, c^1) - e(c^1, c^2))}{P(c^1|d)} \geq \frac{e(c^2, c^2) - e(c^2, c^1)}{e(c^1, c^1) - e(c^1, c^2)}
\]
Two Class Bayes Rule: Odd’s Ratio

Assign to class $c^1$ if

$$\frac{P(c^1|d)}{P(c^2|d)} \geq \frac{e(c^2, c^2) - e(c^2, c^1)}{e(c^1, c^1) - e(c^1, c^2)}$$

Otherwise assign to class $c^2$.

The odd’s ratio $R$ in favor of class $c^1$ is defined by

$$R(d) = \frac{P(c^1|d)}{P(c^2|d)}$$

Assign to class $c^1$ if

$$R(d) \geq \frac{e(c^2, c^2) - e(c^2, c^1)}{e(c^1, c^1) - e(c^1, c^2)} \geq \Theta$$
The likelihood ratio in favor of class $c^1$ is defined by

$$L(d) = \frac{P(d|c^1)}{P(d|c^2)}$$

Assign to class $c^1$ if

$$\frac{P(c^1|d)}{P(c^2|d)} \geq \frac{e(c^2, c^2) - e(c^2, c^1)}{e(c^1, c^1) - e(c^1, c^2)}$$

$$\frac{P(c^1|d)P(d)}{P(c^1)} \geq \frac{e(c^2, c^2) - e(c^2, c^1)}{e(c^1, c^1) - e(c^1, c^2)}$$

$$L(d) = \frac{P(d|c^1)}{P(d|c^2)} \geq \frac{e(c^2, c^2) - e(c^2, c^1)}{e(c^1, c^1) - e(c^1, c^2)}$$

$$\frac{P(c^1)}{P(c^2)} \geq \Theta$$
Two Class Bayes Rule: Class Conditional Probability

Assign to class $c^1$ if

$$P(c^1|d)e(c^1, c^1) + P(c^2|d)e(c^2, c^1) \geq P(c^1|d)e(c^1, c^2) + P(c^2|d)e(c^2, c^2)$$

Otherwise assign to class $c^2$.

$$P(c^1|d)(e(c^1, c^1) - e(c^1, c^2)) \geq P(c^2|d)(e(c^2, c^2) - e(c^2, c^1))$$

$$P(c^1|d)(e(c^1, c^1) - e(c^1, c^2)) \geq (1 - P(c^1|d))(e(c^2, c^2) - e(c^2, c^1))$$

$$P(c^1|d)(e(c^1, c^1) - e(c^1, c^2) + e(c^2, c^2) - e(c^2, c^1)) \geq e(c^2, c^2) - e(c^2, c^1)$$

$$P(c^1|d) \geq \frac{e(c^2, c^2) - e(c^2, c^1)}{e(c^1, c^1) - e(c^1, c^2) + e(c^2, c^2) - e(c^2, c^1)}$$

$$\geq \Theta$$
Given measurement $d$, assign to any class $c^k$ satisfying

$$\sum_{j=1}^{K} e(c^j, c^k) P_T(c^j|d) \geq \sum_{j=1}^{K} e(c^j, c^n) P_T(c^j|d), n = 1, \ldots, K$$

Therefore, the only probability information we need for a Bayes rule are the conditional probabilities

$$P_T(c^j|d), j = 1, \ldots, K$$
Summary

\[ P_T(c \mid d) = \frac{P_T(d \mid c)P(c)}{P(d)} = \frac{P_T(d \mid c)P(c)}{\sum_{\gamma \in C} P_T(d \mid \gamma)P(\gamma)} \]

- For a given \( c \), \( P_T(d \mid c) \) is the class conditional distribution
- \( P_T(c) \) is the prior probability of class \( c \)

Estimating \( P_T(d \mid c) \) from data is a major problem in Machine Learning
Two Class Bayes Rule: Odd’s Ratio

Assign to class \( c^1 \) if

\[
\frac{P(c^1|d)}{P(c^2|d)} \geq \frac{e(c^2, c^2) - e(c^2, c^1)}{e(c^1, c^1) - e(c^1, c^2)}
\]

Otherwise assign to class \( c^2 \).

The odd’s ratio \( R \) in favor of class \( c^1 \) is defined by

\[
R(d) = \frac{P(c^1|d)}{P(c^2|d)}
\]

Assign to class \( c^1 \) if

\[
R(d) \geq \frac{e(c^2, c^2) - e(c^2, c^1)}{e(c^1, c^1) - e(c^1, c^2)} \geq \Theta
\]
The Likelihood ratio in favor of class $c^1$ is defined by

$$
\mathcal{L}(d) = \frac{P(d|c^1)}{P(d|c^2)}
$$

Assign to class $c^1$ if

$$
\mathcal{L}(d) = \frac{P(d|c^1)}{P(d|c^2)} \geq \frac{e(c^2, c^2) - e(c^2, c^1)}{e(c^1, c^1) - e(c^1, c^2)} \frac{P(c^2)}{P(c^1)} \Theta
$$
Two Class

\[ P(c^1|d) \geq \frac{e(c^2, c^2) - e(c^2, c^1)}{e(c^1, c^1) - e(c^1, c^2) + e(c^2, c^2) - e(c^2, c^1)} \geq \Theta \]
Estimating $P_T(d \mid c)$ from data is a major problem in Machine Learning.
Mid Term Project Part 1

- Measurement Space $D = \bigotimes_{n=1}^{N} L_n$
  - Measurement $d$ has $N$ components $d = (d_1, \ldots, d_N)$
  - Input $|L_n| = M_n$, $n = 1, \ldots, N$

- Given $(d_1, \ldots, d_N)$ compute the linear address

- Input $K$, The Number of Classes

- Input $e$ the $K \times K$ economic gain matrix

- Input $P(d \mid c)$ the class conditional probabilities

- Input $P(c)$ the prior probabilities

- Compute $P(c \mid d)$

- Compute the Discrete Bayes Rule $f_d(c)$

- Compute the $K \times K$ Confusion Matrix

- Compute the Expected Gain