Bayesian Statistics and Singular Learning Theory

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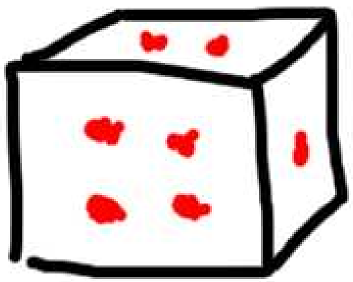
Bayesian Statistics

Two main *interpretations*
of probability theory:
Frequentist and *Bayesian*.

These interpretations do not affect
the *correctness* of probability theory,
but they greatly affect
the *statistical methodology*.

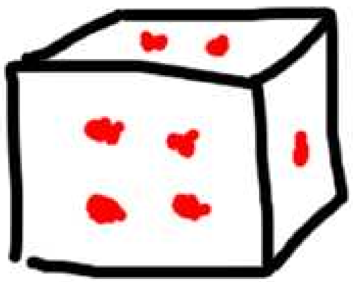


FREQUENTIST:

each number occurs about N/6 times out of N throws of the die.

BAYESIAN:

No, not really. That's only what you BELIEVE about the die.

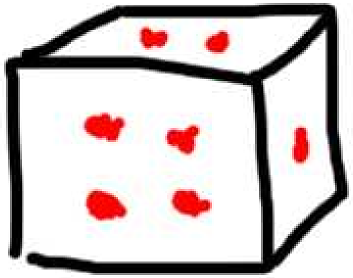


FREQUENTIST:

surely, the die has some inherent probabilities and our purpose is to discover them!!

BAYESIAN:

Nope! These probabilities are not inherent. A die is a die. That's it. But as we observe the die, our belief about its outcomes changes too.



FREQUENTIST:

You are insane!

BAYESIAN:

Not really. That's just what you BELIEVE

Bayes' Rule

$$\boxed{P(A|B)} = \frac{P(B|A)}{P(B)} \boxed{P(A)}$$

posterior
"new belief"

prior
"old belief"

$$P(B) = \sum_i P(B|A_i)P(A_i)$$ normalization constant

Bayes' Rule

Example: A coin, which we believe with
$\frac{9}{10}$ probability to be fair such that $P(H)=\frac{1}{2}, P(T)=\frac{1}{2}$,
$\frac{1}{10}$ probability to be biased such that $P(H)=\frac{3}{4}, P(T)=\frac{1}{4}$.

After observing 8 heads and 2 tails,

$$P(\text{fair}|\text{data}) = \frac{P(\text{data}|\text{fair})}{P(\text{data})} P(\text{fair})$$

$$= \frac{(\frac{1}{2})^8(\frac{1}{2})^2(\frac{9}{10})}{(\frac{1}{2})^8(\frac{1}{2})^2(\frac{9}{10}) + (\frac{3}{4})^8(\frac{1}{4})^2(\frac{1}{10})} = \frac{1024}{1753} \approx 0.584$$

Old belief = $0.900 \longrightarrow$ New belief = 0.584

Statistical Model

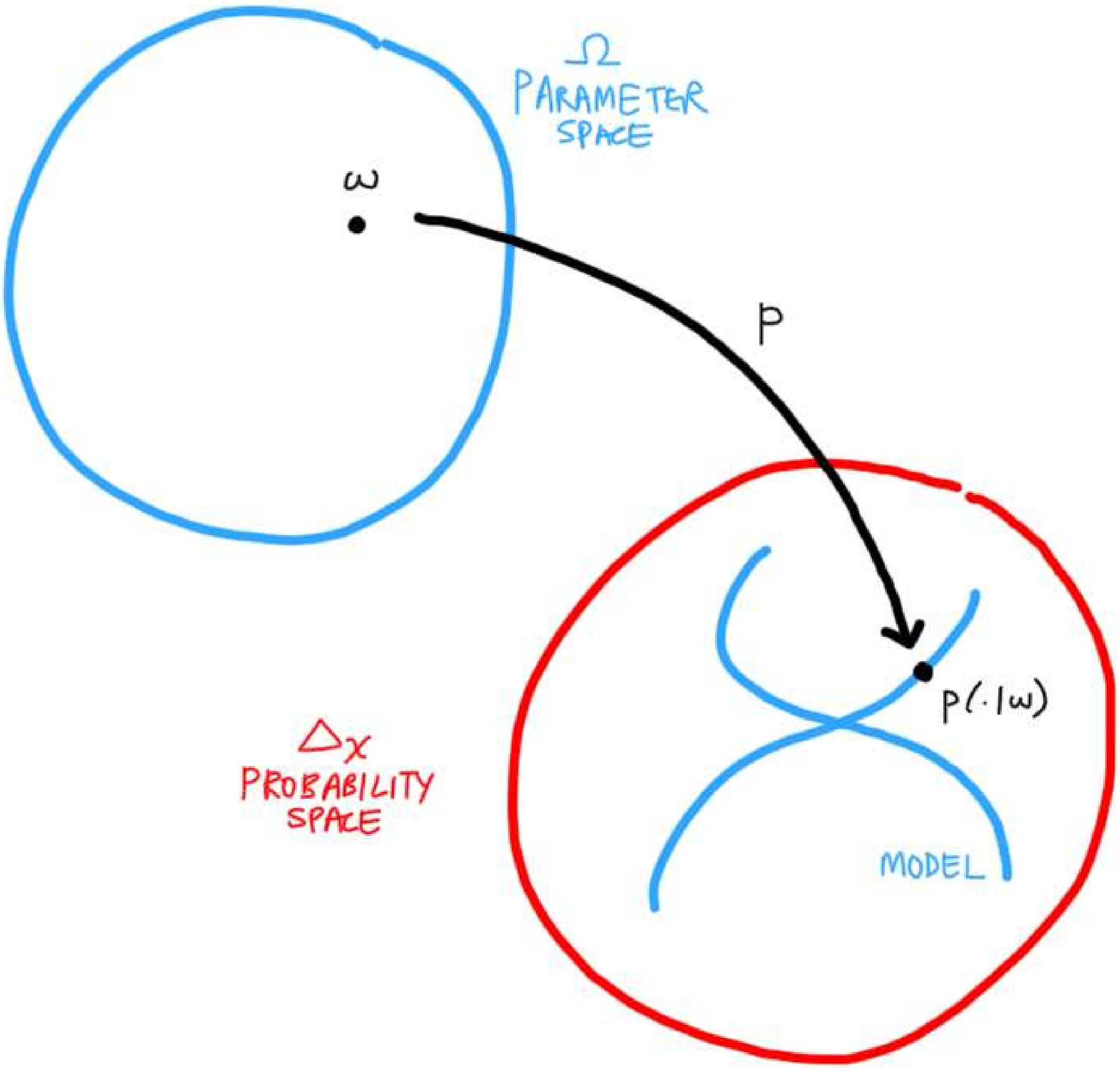
Let X be a random variable with state space $\mathcal{X}$ (e.g. $\{1, 2, \ldots, k\}$, $\mathbb{R}^k$).
Let $X_1, \ldots, X_N$ be N independent random samples of X.

In the previous example, we studied *two* probability distributions, and our beliefs about each of them. More generally, let us study a *family* $\mathcal{M}$ of probability distributions parametrized by some space Ω. Such a family is called a *statistical model*.

In *algebraic statistics*, we think of the statistical model as a map from the *parameter space* Ω to the *probability space* $\Delta_{\mathcal{X}}$.
Let $p(x|\omega)dx$ denote the distribution corresponding to $\omega \in \Omega$.

To each $\omega \in \Omega$, we associate a *belief* about the parameter.
This belief is called the *prior distribution* and is denoted by $\varphi(\omega)d\omega$.
Also, if we are studying more than one model, say $\mathcal{M}_1$ and $\mathcal{M}_2$, we may associate *priors* $p(\mathcal{M}_1)$ and $p(\mathcal{M}_2)$ to each of them.

Statistical Model



Posterior distributions

Recall *prior* = "old belief", *posterior* = "new belief".

Posterior distribution on Ω

$$p(\omega|X_1,\dots,X_N) = \frac{\left(\prod_{i=1}^N p(X_i|\omega)\right)\varphi(\omega)}{\int_\Omega \left(\prod_{i=1}^N p(X_i|\omega)\right)\varphi(\omega)\,d\omega}$$

Posterior distribution on models $\mathcal{M}_1, \mathcal{M}_2$

$$p(\mathcal{M}|X_1,\dots,X_N) = p(\mathcal{M})\int_\Omega \left(\prod_{i=1}^N p(X_i|\omega)\right)\varphi(\omega)\,d\omega$$

Model Selection

Frequentist:
"I want to find the *best parameter* ω which describes the data."

Maximum Likelihood: Pick the model that maximizes

$$\max_{\omega} \prod_{i=1}^{N} p(X_i|\omega)$$

Bayesian:
"Which model do I *believe in the most* after the observing data?"

Marginal Likelihood: Pick the model that maximizes

$$p(\mathcal{M}) \int_{\Omega} \left(\prod_{i=1}^{N} p(X_i|\omega) \right) \varphi(\omega)\, d\omega$$

An *important and difficult* problem in Bayesian statistics is the *accurate approximation* of the marginal likelihood integral.

Singular Learning Theory

A statistical model is *regular* if it is identifiable
and its Fisher information matrix is postive definite.
Behavior of regular models for large samples is
well-understood, e.g. *central limit theorems*.

A model is *singular* if it is not regular.
Many hidden variable models are singular.
Singular learning theory teaches us how to study
the *asymptotic behavior* of singular models:
by monomializing the Kullback-Leibler distance.

The True Distribution

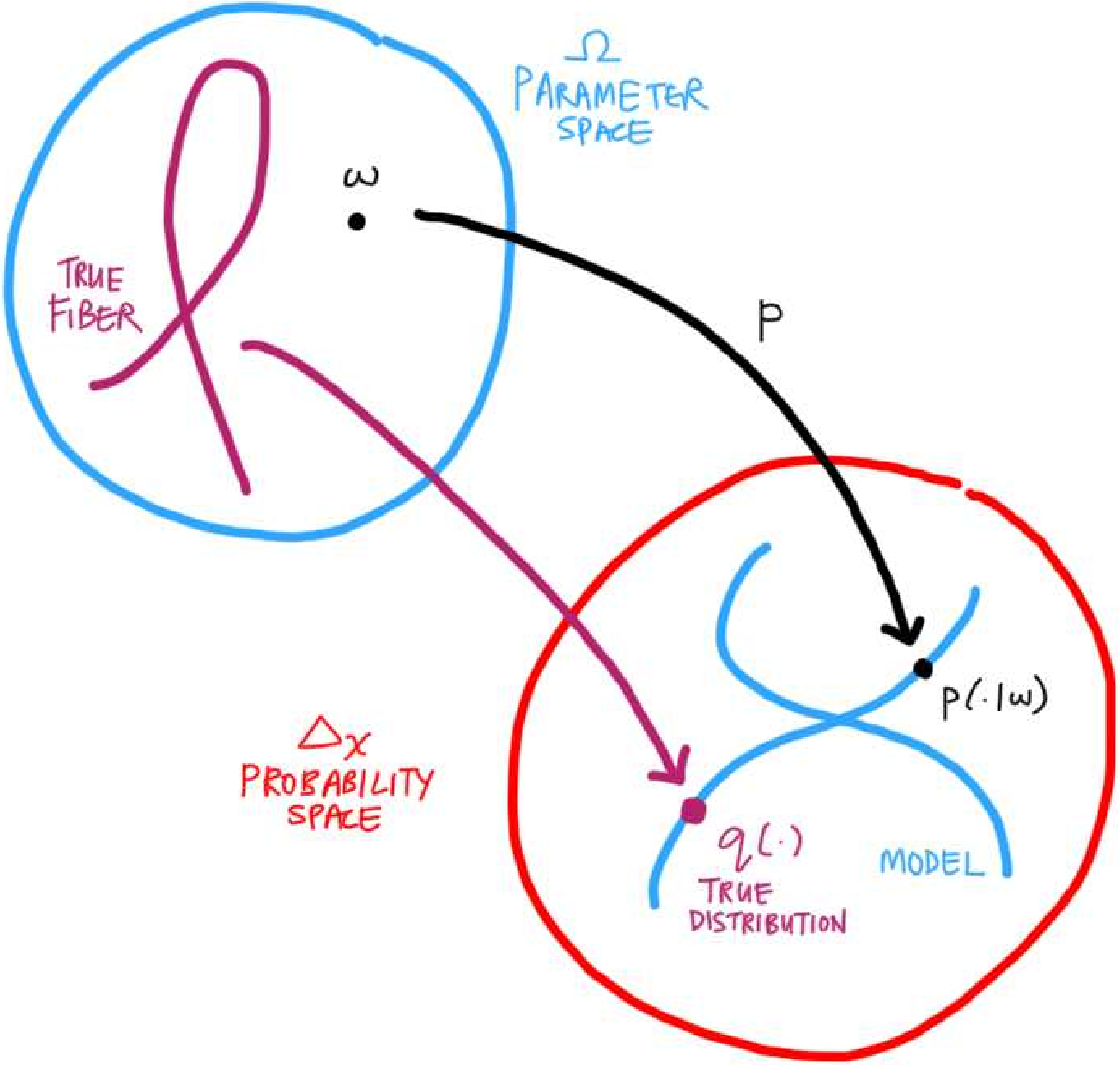
Let X be a random variable.
In *statistical learning theory*, we are interested in using the data $X_1, \ldots, X_N$ to select a model $\mathcal{M}$ that best describes X.
For this purpose, many *model selection criteria* (e.g. maximum likelihood, marginal likelihood, AIC, BIC) have been designed.

It is important to analyze how these criteria behave as the *number of samples grow large*. For this purpose, we need to assume that X has a *true distribution* $q(x)dx$.
Given a model, let the *true fiber* be the set of all parameters $\omega \in \Omega$ which map to the true distribution.

Remark:

The word "true distribution" disturbs the Bayesian in us, but we disregard such philosophical objections for now.
I like to think of X as a computer (black box) producing outputs $X_1, \ldots, X_N$ according to a fixed procedure $q(x)dx$ in some model $\mathcal{M} \in \{\mathcal{M}_1, \ldots, \mathcal{M}_K\}$.
My goal is to select the right $\mathcal{M} \in \{\mathcal{M}_1, \ldots, \mathcal{M}_K\}$ by using the outputs.

Statistical Model



Kullback-Leibler distance

Given a model, recall that the *likelihood* of the data is

$$L_N(\omega) = \prod_{i=1}^{N} p(X_i|\omega).$$

To compare the model distribution with the true distribution, we have the *log likelihood ratio*

$$K_N(\omega) = \frac{1}{N} \log \frac{\prod_{i=1}^{N} q(X_i)}{\prod_{i=1}^{N} p(X_i|\omega)} = \frac{1}{N} \sum_{i=1}^{N} \log \frac{q(X_i)}{p(X_i|\omega)}.$$

In fact, the expectation of $K_N(\omega)$ over the data distribution is the *Kullback-Leibler distance*

$$K(\omega) = \int_{\mathcal{X}} q(x) \log \frac{q(x)}{p(x|\omega)} dx.$$

In statistics, this distance is an important measure of the difference between two distributions.

Regular and Singular Models

Suppose $q(x)dx$ equals $p(x|\omega_0)dx$ for some $\omega_0 \in \Omega$.

The model is *identifiable* at ω_0 if the true fiber has only one point.

The *Fisher information matrix* $I(\omega_0)$ is the Hessian matrix of the KL distance $K(\omega)$ at ω_0. This matrix is always *positive semidefinite*.

A model is *regular* if it is identifiable and the Fisher information matrix $I(\omega)$ is *positive definite* at all $\omega \in \Omega$.

A model is *singular* if it is not regular. In particular, singular models are either nonidentifiable, or $\det I(\omega) = 0$ for some $\omega \in \Omega$.

The asymptotic behavior of regular models is well-understood.
[See Schwarz(1978), Haughton(1988), Lauritzen(1996).]
Unfortunately, many important models in learning theory are singular.

Asymptotic Behavior

To analyze the *asymptotic behavior* of model selection criteria, we often need to understand the *log likelihood ratio* $K_N(\omega)$.

e.g. Marginal likelihood

$$Z_N = \int_\Omega \prod_{i=1}^{N} p(X_i|\omega)\varphi(\omega)d\omega = \prod_{i=1}^{N} q(X_i) \cdot \int_\Omega e^{-NK_N(\omega)}\varphi(\omega)d\omega$$

e.g. For regular models, the Bayesian Information Criterion (BIC) uses the approximation $-\log Z_N \approx -\log L_N^* + \frac{d}{2}\log N$ for model selection. Here, L_N^* is the maximum likelihood and d the model dimension.

Watanabe showed that the *log likelihood ratio* $K_N(\omega)$ can be put in a nice standard form if we resolve the singularities of the *Kullback-Leibler distance* $K(\omega)$.

Resolution of Singularities

Watanabe's insight: find a change of variables $\rho : \mathscr{M} \to \Omega$
such that $K(\omega)$ becomes *locally monomial* on the *manifold* $\mathscr{M}$.

Such a change of variables always exists, due to a deep theorem in algebraic geometry known as *resolution of singularities*. [Proved in 1964, this theorem won Hironaka the Fields Medal.]

Standard Form of Log Likelihood Ratio (Watanabe)

Given mild conditions on the model $\mathcal{M}$, there exists a change of variable $\rho : \mathscr{M} \to \Omega$ such that (μ^κ denotes $\mu_1^{\kappa_1} \cdots \mu_d^{\kappa_d}$)

$$K_N(\rho(\mu)) = \mu^{2\kappa} - \frac{1}{\sqrt{N}} \mu^\kappa \xi_N(\mu)$$

where $\xi_N(\mu)$ converges in law to a Gaussian process on $\mathscr{M}$.

This is the *generalized Central Limit Theorem* for singular models.

Learning Coefficient

Define empirical entropy $S_N = -\frac{1}{N}\sum_{i=1}^{N} \log q(X_i)$.

Convergence of stochastic complexity (Watanabe)

Given mild conditions on the model $\mathcal{M}$, the stochastic complexity $-\log Z_N$ has the asymptotic expansion

$$-\log Z_N = NS_N + \lambda \log N - (\theta - 1) \log \log N + F_N^R$$

where F_N^R converges in law to a random variable. Moreover, λ is the smallest pole, and θ its order, of the zeta function

$$\zeta(z) = \int_\Omega K(\omega)^{-z} \varphi(\omega) d\omega, \quad z \in \mathbb{C}.$$

This is the *generalized BIC* for singular models.

We call λ the *learning coefficient* of the model $\mathcal{M}$ at the true distribution, and θ its *order*. We compute them by *monomializing* $K(\omega)$ and $\varphi(\omega)$.

Computing the Learning Coefficient

Suppose $K(\omega) = \omega_1^{\kappa_1} \cdots \omega_d^{\kappa_d}$, $\varphi(\omega) = \omega_1^{\tau_1} \cdots \omega_d^{\tau_d}$ and $\Omega = [0, \varepsilon]^d$.

Then, the zeta function is

$$\begin{aligned} \zeta(z) &= \int_{[0,\varepsilon]^d} \omega_1^{-\kappa_1 z + \tau_1} \cdots \omega_d^{-\kappa_d z + \tau_d} \, d\omega \\ &= \frac{\varepsilon^{-\kappa_1 z + \tau_1 + 1}}{-\kappa_1 z + \tau_1 + 1} \cdots \frac{\varepsilon^{-\kappa_d z + \tau_d + 1}}{-\kappa_d z + \tau_d + 1} \end{aligned}$$

The poles of this function are $(\tau_i + 1)/\kappa_i$ for each i.

Thus, the learning coefficient is given by

$$\lambda = \min_i \frac{\tau_i + 1}{\kappa_i}$$

and its order θ is the number of times this minimum is attained.

The most *difficult* computation
in singular learning
is *finding* a change of variables
which monomializes $K(\omega)$.

Real Log Canonical Thresholds

The Kullback-Leibler distance $K(\omega)$
is a *nonpolynomial* function that is
computationally difficult to monomialize.

Many singular models, however,
are regular models whose parameters are
polynomial functions of new parameters.

We want to *exploit* this polynomiality
in computing their learning coefficients.

Regularly Parametrized Models

A model $\mathcal{M}$ is *regularly parametrized* if it can be expressed as a regular model whose parameters $u = (u_i)$ are analytic functions $u_i(\omega)$ of new parameters $\omega = (\omega_i)$.

e.g. Discrete models $\quad (p_1(\omega), p_2(\omega), \ldots, p_k(\omega))$
Gaussian models $\quad X \sim \mathcal{N}(\mu, \Sigma)$, $\mu = (\mu_i(\omega))$, $\Sigma = (\sigma_{ij}(\omega))$

Suppose the true distribution lies in the model $\mathcal{M}$, i.e. $q(x) = p(x|\omega^*)$ for some $\omega^* \in \Omega$.

Define the *fiber ideal* $I = \langle u_i(\omega) - u_i(\omega_i^*)$ for all $i\rangle$.
It is the ideal of the *true fiber* $V = \{\omega \in \Omega \mid q(x) = p(x|\omega)$ for all $x\}$.

Real Log Canonical Thresholds

In algebraic geometry, the *real log canonical threshold* of an ideal $\langle f_1(\omega), \ldots, f_k(\omega) \rangle$ is the pair (λ, θ) where λ is the smallest pole of the zeta function

$$\zeta(z) = \int_\Omega (f_1^2(\omega) + \cdots + f_k^2(\omega))^{-z/2} \, |\varphi(\omega)| d\omega$$

and θ its order. We denote $(\lambda, \theta) = \mathrm{RLCT}_\Omega(I; \varphi)$.

- This definition is independent of the choice of generators for I.
- Fix I, Ω and φ. For each point $x \in \Omega$, there exists a sufficiently small open neighborhood Ω_x of x in Ω such that $\mathrm{RLCT}_U(I; \varphi)$ is the same for all open neighborhoods U of x contained in Ω_x.
- We order the pairs (λ, θ) by the value of $\lambda \log N - (\theta - 1) \log \log N$ for sufficiently large N.

Exploiting Polynomiality

Theorem (L.)

Let $\mathcal{M}$ be a regularly parametrized model, and let the true distribution $q(x)dx$ be in $\mathcal{M}$. Given mild conditions on $\mathcal{M}$, the learning coefficient λ and its order θ of the model is given by

$$(2\lambda, \theta) = \min_{x \in \mathcal{V}(I)} \mathrm{RLCT}_{\Omega_x}(I; \varphi)$$

where I is the fiber ideal at the true distribution and $\mathcal{V}(I) \subset \Omega$ is the true fiber.

Newton Polyhedra

Given an ideal $I \subset \mathbb{R}[\omega_1, \ldots, \omega_d]$,

1. Plot $\alpha \in \mathbb{R}^d$ for each monomial ω^α appearing in some $f \in I$.
2. Take the convex hull $\mathcal{P}(I)$ of all plotted points.

This convex hull $\mathcal{P}(I)$ is the *Newton polyhedron* of I.

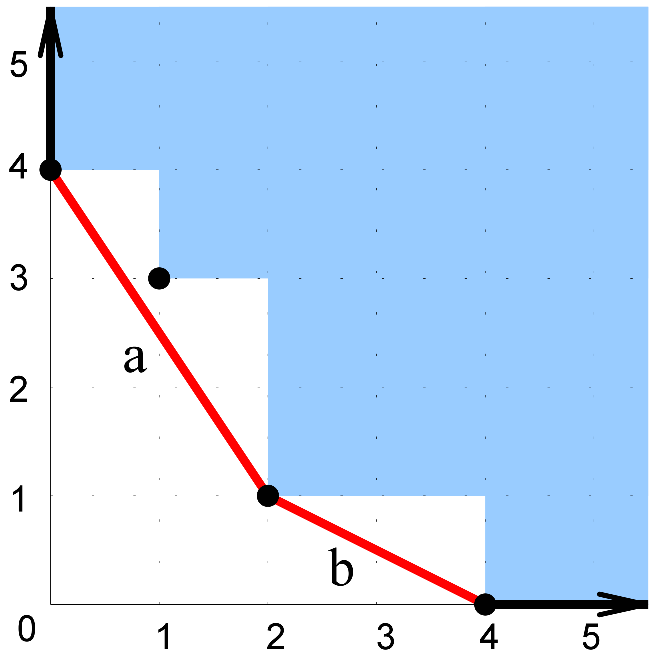
Given a vector $\tau \in \mathbb{Z}^d_{\geq 0}$, define

1. *τ-distance* l_τ : smallest $t \geq 0$ such that $t(\tau_1 + 1, \ldots, \tau_d + 1) \in \mathcal{P}(I)$.
2. *multiplicity* θ_τ : codimension of face of $\mathcal{P}(I)$ at this intersection.

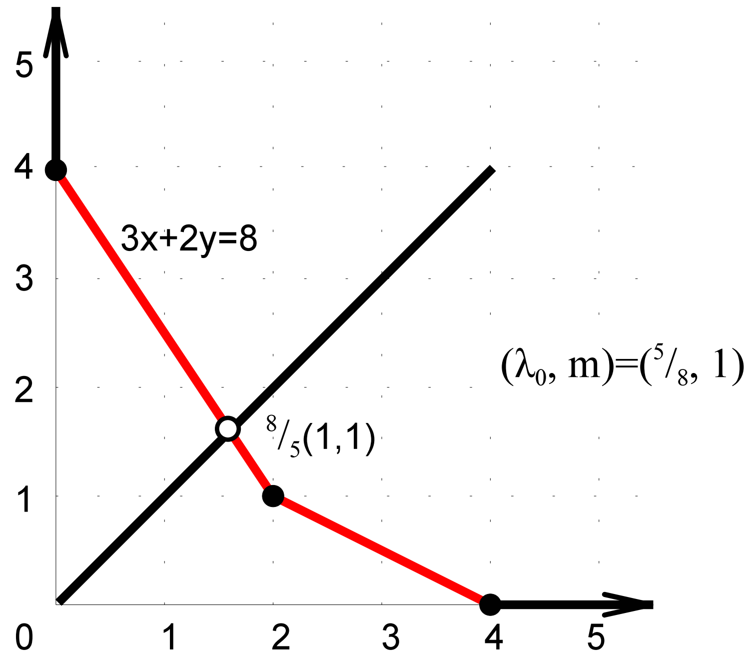
Newton Polyhedra

Let $I = \langle x^4, x^2y, xy^3, y^4 \rangle$ and $\tau = (0,0)$.

Newton polyhedron



τ-distance



The τ-distance is $l_\tau = 8/5$ and the multiplicity is $\theta_\tau = 1$.

Bounding the RLCT

Theorem (L.)

Let $I \subset \mathbb{R}[\omega_1, \ldots, \omega_d]$ be a finitely generated ideal, and $U \subset \mathbb{R}^d$ a sufficiently small nbhd of the origin. Then,

$$\mathrm{RLCT}_U(I; \omega^\tau) \leq (1/l_\tau, \theta_\tau)$$

where l_τ is the τ-distance of the Newton polyhedron $\mathcal{P}(I)$ and θ_τ its multiplicity. Equality occurs when I is a monomial ideal.

Using this theorem, we can compute the RLCT of *any* ideal by monomializing the ideal.

Examples

Example 1: Bayesian Information Criterion

When the model is regular, the fiber ideal is $I = \langle \omega_1, \ldots, \omega_d \rangle$.
Using Newton polyhedra, the RLCT of this ideal is $(d, 1)$.

By our theorem, the learning coefficient is $(\lambda, \theta) = (d/2, 1)$.
By Watanbe's theorem, the stochastic complexity is asymptotically

$$NS_N + \frac{d}{2} \log N.$$

This formula is the *Bayesian Information Criterion* (BIC).

Examples

Example 2: **132 Schizophrenic Patients**

Evans-Gilula-Guttman(1989) studied schizophrenic patients for connections between recovery time (in years Y) and frequency of visits by relatives.

	$2 \leq Y < 10$	$10 \leq Y < 20$	$20 \leq Y$	*Totals*
Regularly	43	16	3	*62*
Rarely	6	11	10	*27*
Never	9	18	16	*43*
Totals	*58*	*45*	*29*	**132**

They wanted to find out if the data can be explained by a *naïve Bayesian network* with two hidden states (e.g. male and female).

Examples

Example 2: **132 Schizophrenic Patients**

The model is parametrized by $(t, a, b, c, d) \in \Delta_1 \times \Delta_2 \times \Delta_2 \times \Delta_2 \times \Delta_2$.

	$2 \leq Y < 10$	$10 \leq Y < 20$	$20 \leq Y$
Regularly	$ta_1b_1 + (1-t)c_1d_1$	$ta_1b_2 + (1-t)c_1d_2$	$ta_1b_3 + (1-t)c_1d_3$
Rarely	$ta_2b_1 + (1-t)c_2d_1$	$ta_2b_2 + (1-t)c_2d_2$	$ta_2b_3 + (1-t)c_2d_3$
Never	$ta_3b_1 + (1-t)c_3d_1$	$ta_3b_2 + (1-t)c_3d_2$	$ta_3b_3 + (1-t)c_3d_3$

As a model selection criteria, we compute the *marginal likelihood* of this model, given the above data and a uniform prior on the parameter space.

Examples

Example 2: **132 Schizophrenic Patients**

Lin-Sturmfels-Xu(2009) computed this integral *exactly*.
It is the rational number with numerator

$$
\begin{array}{l}
278019488531063389120643600324989329103876140805 \\
285242839582092569357265886675322845874097528033 \\
99493069713103633199906939405711180837568853737
\end{array}
$$

and denominator

$$
\begin{array}{l}
12288402873591935400678094796599848745442833177572204 \\
50448819979286456995185542195946815073112429169997801 \\
33503900169921912167352239204153786645029153951176422 \\
43298328046163472261962028461650432024356339706541132 \\
34375318471880274818667657423749120000000000000000.
\end{array}
$$

Examples

Example 2: **132 Schizophrenic Patients**

We want to approximate the integral using asymptotic methods.
The EM algorithm gives us the *maximum likelihood distribution*

$$q = \frac{1}{132} \begin{pmatrix} 43.002 & 15.998 & 3.000 \\ 5.980 & 11.123 & 9.897 \\ 9.019 & 17.879 & 16.102 \end{pmatrix}.$$

Compare this distribution with the data

$$\begin{pmatrix} 43 & 16 & 3 \\ 6 & 11 & 10 \\ 9 & 18 & 16 \end{pmatrix}.$$

We use the ML distribution as the *true distribution* for our approximations.

Examples

Example 2: **132 Schizophrenic Patients**

Recall that stochastic complexity $= -\log$ (marginal likelihood).

- The BIC approximates the stochastic complexity as

$$NS_N + \frac{9}{2}\log N.$$

- By computing the RLCT of the fiber ideal, our approximation is

$$NS_N + \frac{7}{2}\log N.$$

- Summary:

	Stochastic Complexity
Exact	273.1911759
BIC	278.3558034
RLCT	275.9144024

“Algebraic Methods for Evaluating Integrals in Bayesian Statistics”

http://math.berkeley.edu/~shaowei/swthesis.pdf

(PhD dissertation, May 2011)

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