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Confidence sets for binary classification problems

Author: Noémi Takács

Supervisor: Ambrus Tamás SZTAKI, ELTE

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Topic of the project

Previous semester:

- confidence intervals for mean estimates
- preparation for binary classification

Aim of the second semester:

- **e**stimate the regression function (f_*) in binary classification
- construct confidence sets around the estimation

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Binary cla	assification			

It is given an i.i.d. sample: $(X, Y) \in \mathbb{X} \times \mathbb{Y}$, where $\mathbb{X} \subseteq \mathbb{R}^d$ and $\mathbb{Y} = \{1, -1\}$.

Definition

The (measurable) $g : \mathbb{X} \to \mathbb{Y}$ classifier is Bayes optimal, if it minimizes the Bayes risk $R(g) \doteq E[L(Y, g(X))]$, where *L* is a nonnegative measurable loss function.

If $L(Y, g(X)) = \mathbb{I}(Y \neq g(X))$, where \mathbb{I} is the indicator function, then the Bayes optimal classifier will be the sign of the regression function,

$$f_*(x) \doteq E[Y|X = x] = 2 \cdot P(Y = 1|X = x) - 1.$$

$$P(Y = 1 | X = x) = \frac{P(Y = 1) \cdot f_{X|Y=1}(x)}{P(Y = 1) \cdot f_{X|Y=1}(x) + P(Y = -1) \cdot f_{X|Y=-1}(x)}.$$

Generalization of SPS method

- \rightarrow distribution-free
- \rightarrow non-asymptotic

Assumptions:

- $X \subseteq \mathbb{R}^d$ and the $\{(X_j, Y_j)\}_{j=1}^n$ sample is i.i.d.;
- for the regression function a parameterised family \mathcal{F} is given, which contains f_* ;
- the parameterisation is injective, such that for all $\theta_1 \neq \theta_2 \in \Theta$:

$$\|f_{\theta_1} - f_{\theta_2}\|_P^2 \doteq \int_{\mathbb{X}} (f_{\theta_1}(x) - f_{\theta_2}(x))^2 dP_X(x) \neq 0.$$

Main idea:

- for a given θ generate m-1 alternative samples $\mathcal{D}_i(\theta)$
- \blacksquare compare the original \mathcal{D}_0 and the alternative samples with a ranking function
- \blacksquare construct the confidence set based on the rank of \mathcal{D}_0

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The conf	idence set			

Theorem

Under the mentioned, mild statistical assumptions, the confidence set contains f_* with exact user-chosen inclusion probability.

Remark

If $\theta = \theta^*$, then \mathcal{D}_0 and $\mathcal{D}_i(\theta^*)$ comes from the same distribution.

2 If $\theta \neq \theta^*$, then the distribution of $\mathcal{D}_i(\theta)$ differs from that \mathcal{D}_0 .

Hypothesis testing:

 $H_0: f_* = f_\theta$ $H_1: f_* \neq f_\theta$

Acceptance region: the confidence set

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Generated mixed Laplace distributions I.

Parameters used for the generations:

$$P(Y = 1) = P(Y = -1) = 0.5$$

$$\blacksquare \mu = Y$$

 $\blacksquare \ \lambda = \mathbf{1}$

Tested parameters: p = P(Y = 1) and λ . Fixed location parameters.

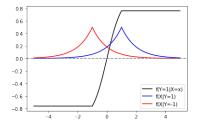


Figure: The two Laplace PDF and the real regression function

First experiment:

- $\mu_1 = 1, \, \mu_2 = -1$ (as known)
- *n* = 500
- *m* = 20 → confidence levels: 5%,...,95%,100%

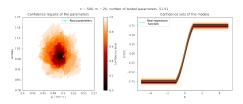


Figure: Different level confidence sets in the parameter and model space

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Generated mixed Laplace distributions II.

Second experiment:

- comparison of the known values and the ML estimates of the location parameters
- $\blacksquare n = 20, 60, 100, 200, 300$
- $m = 10 \rightarrow \text{confidence}$ levels: $10\%, \dots, 90\%, 100\%$
- repeated 5 times
- calculate the mean of the ranks for all tested parameter pairs

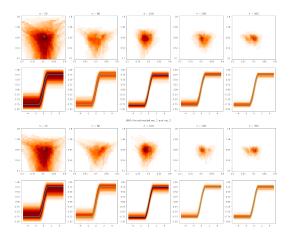


Figure: Mean of the ranks in the parameter and the model space

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Bank churn

- $\blacksquare \ \mathbb{Y} = \{1,0\}$
- P(leaving the bank) ~ age
- two model class: using normal and lognormal distributions

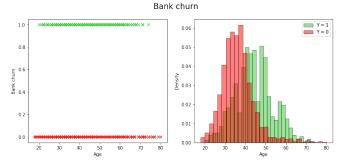


Figure: Illustrations of the observations

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Compare	model classes			

- tested parameters: p and σ_2^2
- fixed parameters: μ₁, μ₂ and σ₁² with ML estimates
- *n* = 4000
- *m* = 10 → confidence levels: 10%,...,90%,100%

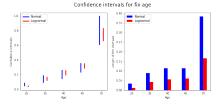


Figure: Confidence intervals and their length for the two model classes

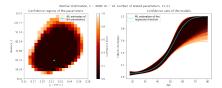


Figure: Results of using normal distributions

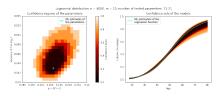


Figure: Results of using lognormal distributions

Monte Carlo sampling

- *n* = 200
- multiple sampling (5 times)
- using lognormal distributions
- tested parameters:
 - $p \text{ and } \sigma_2^2$
 - $\square p \text{ and } \mu_2$
- $m = 10 \rightarrow \text{confidence levels:}$ 10%,...,90%,100%

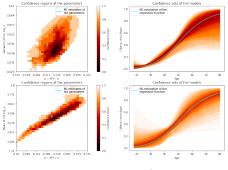


Figure: Mean of the ranks: σ_2^2 vs. μ_2

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Further plans

- Multivariate cases (higher dimension, more parameters)
- Represent the results
- Extract confidence intervals from the sets

References



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Thank you for your attention!