HOW DO THE PROPOSED BENCHMARKING MODELS WORK?

Isaac Subirana

Executive Agency for Health and Consumers

C S B Consorci Sanitari de Barcelona

IMAS Institut Municipal d'Assistència Sanitària

IMIM hospitaldelmar

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VARIABLES

- OUTCOME
  - In-hospital mortality (binary)

- PREDICTORS:
  - **Fixed effects variables**
    - At patient level: age, gender, history of diabetes, etc.
    - At hospital level: university, surgery facilities, etc.
    - At country level: gross national income, life expectancy, etc.
  - **Random effects variables**
    - Hospital specific effects (one different effect for each hospital)
    - Country specific effect (one different effect for each country)

SAMPLE DATA STRUCTURE

- **Hierarchical clustering of observations because**
  - Patients admitted in hospitals: **patients nested in hospitals (LEVEL 1)**
  - Hospitals belongs to a country: **hospitals nested in country (LEVEL 2)**

- **Correlations among observations:**

  The outcomes of 2 patients of the same country are correlated, and, if they are admitted to the same hospital, they are even more correlated.

MODEL: assumptions(I)

- Formulation: **logit(p) = μ+βx+H+C**

  - **x**: fixed effect variables vector. Characteristic of patient, hospital and country: e.g. women 55y old, admitted to a university hospital in a country with a life expectancy of 78 years
  - **p**: probability that a patient dies in-hospital given **x**
  - **μ**: baseline in-hospital mortality risk (at logit scale)
  - **β**: coefficient vector of fixed effects variables
  - **H**: hospital specific random effects.
    - $H \sim N(0,\sigma_H)$ independent among hospitals
  - **C**: country specific random effects.
    - $C \sim N(0, \sigma_C)$ independents among countries
  - **H** and **C** are independent between them.

MODEL: assumptions (II)

- Fixed effects predictors + Random effect predictors ➔ MIXED
- Logistic link between predictor variables and mortality risk ➔ LOGISTIC
- **LOGISTIC MIXED REGRESSION MODEL**
- SOFTWARE: lmer function of lme4 package of R sofware (version 2.7 or later)

MODEL advantages

- **Why mixed regression?**
  - It allows us to **deal with correlations** among patients
  - It takes into account **specific differences among countries and among hospitals** not captured by the fixed effects variables at country and hospital levels.
  - It is not possible to incorporate country and hospital specific effects in the “classic way” (fixed effect factors), due to colinearity. They must be introduced as random effects.
  - It is possible to estimate the country and hospital variabilities.

PREDICTION: Formulation (I)

GOAL: predict in-hospital mortality rate for a given hospital.

- After fitting the model to the sample data, estimations of parameters are obtained: $\hat{\mu}$, $\hat{\beta}$, $\hat{\sigma}_C$, $\hat{\sigma}_H$.
  They are used to perform the predictions.

- The given hospital will be always anonymous,
  - ➔ This introduce uncertainty in the prediction
  - ➔ **The prediction will not be a single number but a random variable with a range of probable numbers.**

  - Remember: $\text{logit}(p) = \mu+\beta x+C+H$
    If we don't know the hospital, the value of H is unknown.
    But its distribution is assumed to be $N(0,\sigma_H)$.

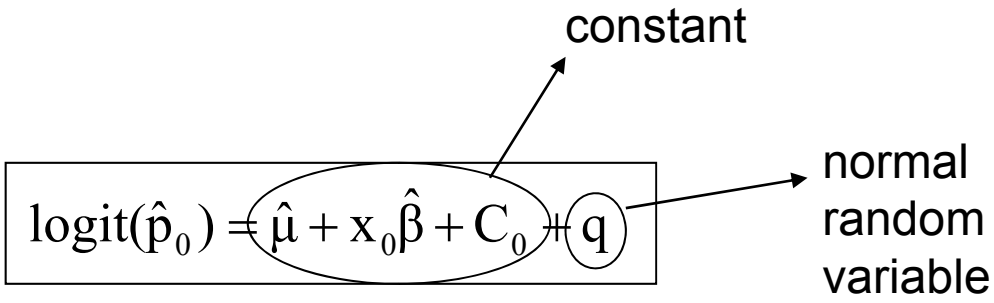
PREDICTION: Formulation (II)

- We need to compute: $\text{logit}(\hat{p}_0) = \hat{\mu} + x_0\hat{\beta} + C_0 + q$

  To define the elements of above equation, two cases must be considered:

- CASE A: The hospital belongs to a country used to fit the model
  - $C_0 = \hat{C}_0$ is the "Bayes estimate" corresponding to the country of the given hospital,
  - $q \sim N(0, \sigma_H)$
- CASE B: The hospital belongs to a country not used to fit the model
  - $C_0=0$,
  - $q \sim N\left(0, \sqrt{\sigma_H^2 + \sigma_C^2}\right)$

PREDICTION: Formulation (III)



- ➔ In both cases $\text{logit}(\hat{p}_0)$ is a normal random variable
  - 1st: compute the percentiles of $\text{logit}(\hat{p}_0)$,
  - 2ond: apply inverse of logit function to obtain the percentiles of $\hat{p}_0$

PREDICTION: Performance

Patient risk → Hospital rate

- The model is built to predict in-hospital mortality risk for a given patient
- We want to predict the in-hospital mortality rate for a given hospital.
- We approximate the last by predicting the in-hospital mortality risk for an average patient of the given hospital.

PREDICTION: Example (I)

As an example, for a given hospital:

- Filter: patients with AMI
- Mean age of patients: 65.1 years old
- Proportion of women: 27.7%
- Percentage of HTN patients: 54.9%
- Percentage of diabetic patients: 26.1%
- Percentage of patients with previous CV disease: 57.9%

PATIENT LEVEL:
AVERAGE PATIENT CHARACT.

- University hospital: YES
- Cath. laboratory: YES
- Coronary surgery facilities: NO

HOSPITAL LEVEL:
HOSPITAL CHARACT.

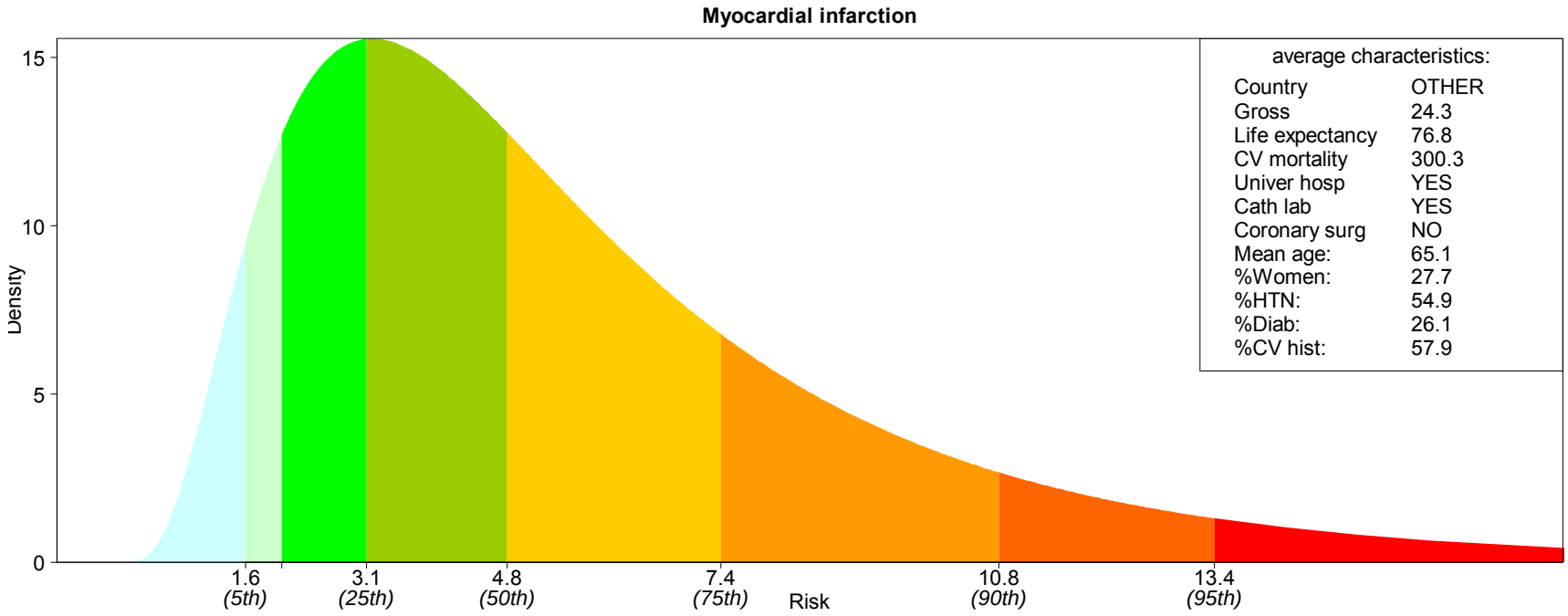
- Country: 'OTHER'
- GROSS: 24.3
- Life expectancy: 76.8
- Age-standardized CV mortality: 300.3

COUNTRY LEVEL:
COUNTRY CHARACT.

If unkown, the average of sample countries are imputed

PREDICTION: Example (II)

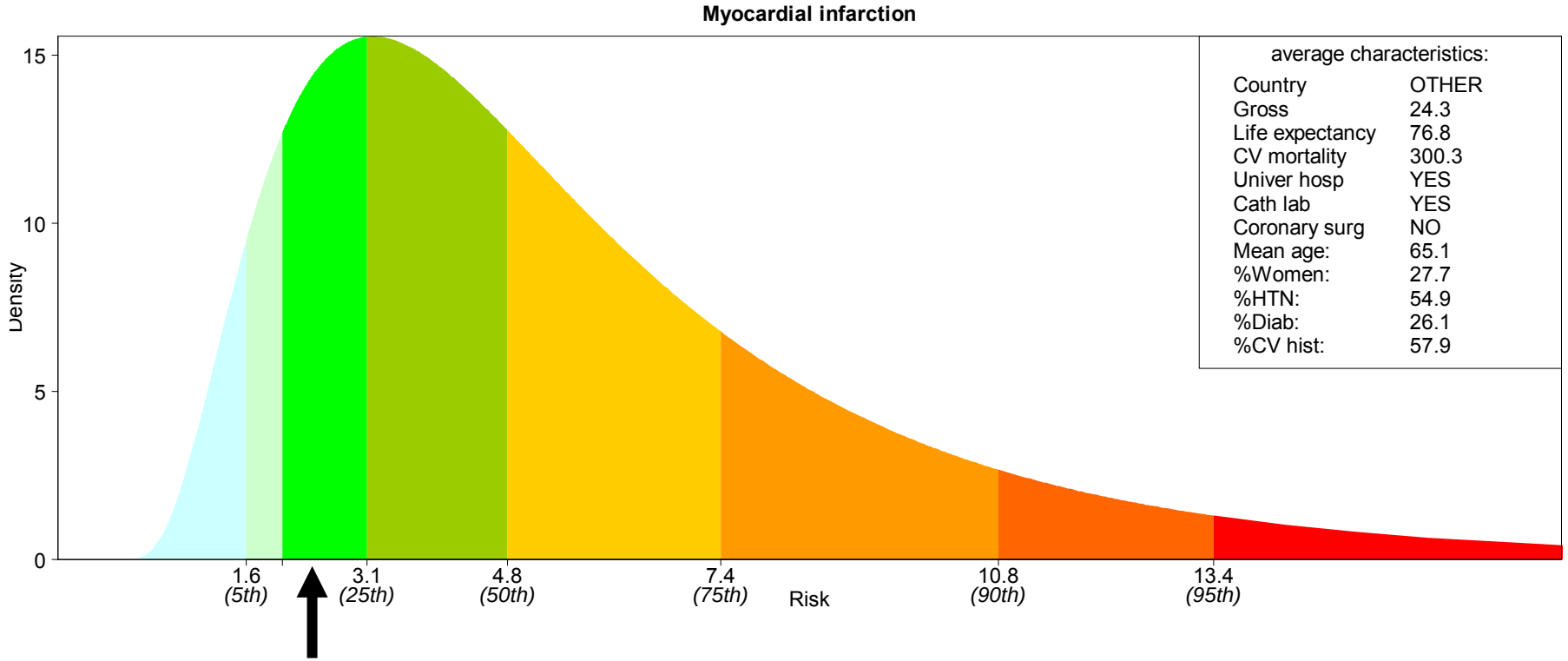
RESULT: The distribution provided by the function of the possible values of the in-hospital AMI mortality rate in this example is:



PREDICTION: Example (III)

- Let's suppose that in this given hospital the observed (actual) in-hospital mortality rate is 2.2%.

PREDICTION: Example (IV)



2.2% observed in-hospital mortality rate

According to the model and the data, this given hospital is in the best quartile of hospitals with the same characteristics (patients and hospital variables) and the same country.

PREDICTION: utility

- We have a reference of what is the expected range of mortality rates in a hospital with the proposed characteristics receiving patients with the described individual characteristics in the corresponding country.

THANK YOU!