# Exam CompStat: 26.7.17 16:00

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- $y_i$, $\hat{y}$ RV
- $< y >= \mu_y$ not random $\rightarrow$ Prior

## 1 Basic Properties of random Variables

- Transitional, cond.prob., joint prob. margin

$$\int p(x,y)dy = f(x)$$

- law of error propagation

$$\sigma_y^2 = \sigma_x^2 * (dy/dx)^2$$
$$P(x|y) = P(x,y)/P(y)$$

## 2 Distributions

- uniform, binomial, poissonian, (multivariate-) gaussian, $\chi^2$, exponential

$$f(x) > 0$$
$$\int f(x)dx = 1$$

- PDF

$$f(x)dx$$

- CDF

$$int(f(x), x, -Inf, y) = g(y)$$

- MGF

$$< e^{tx} >= \int e^{tx} f(x)dx$$

- moments

$$\int x^m f(x)dx$$
$$\int (x-\alpha)^m f(x)dx$$

## 3 Bayes Theorem

- hi

$$P(d,t)$$
$$G(x,\mu) = e^{-\frac{1}{2}\frac{(x-\mu)^2}{\sigma^2}}$$
$$P(D|T) = P(D,T)/P(T)$$
$$P(T|D) = P(D,T)/P(D)$$

- frequentists approach

$$P(D,T) = \dots$$
$$d_i, \hat{d} = \sum_i \frac{d_i}{N} = f \text{ of data}$$
$$< \hat{d} >= \mu$$
$$\rightarrow \text{ PDF}(\hat{\theta}) \text{ (PDF of estimator)}$$

- Bayes Theorem

$$P(T|D) = P(D|T)\frac{P(T)}{P(D)}$$
$$E(D) = \int L(D|T)\pi(T)dT$$
$$B_{a,b} = \frac{E_a(D)}{E_b(D)}$$

## 4 Fisher Estimation

$$F_{\alpha,\beta} = \left.\frac{\partial^2 log(L)}{\partial\theta_\alpha \partial\theta_\beta}\right|_{L_{max}}$$

- we assume gaussian distributed parameters around the peak for a found maximum likelihood estimator

$$e^{-\frac{1}{2}(x_i-\mu_i)C^{-1}_{i,j}(x_j-\mu_j)}$$

## 5 fitting

$$t = f(x) = A_0 + A_1 f_1(x) + A_2 f_2(x)$$
$$e^{-\frac{1}{2}\sum_i \frac{(d_i-t_i)^2}{\sigma_i^2}} \Rightarrow C_{i,j}$$
$$A|_{L_{max}} = G^{-1}D, F_{\alpha,\beta} = G$$