

Prediction intervals based on historical controls for the micronucleus test

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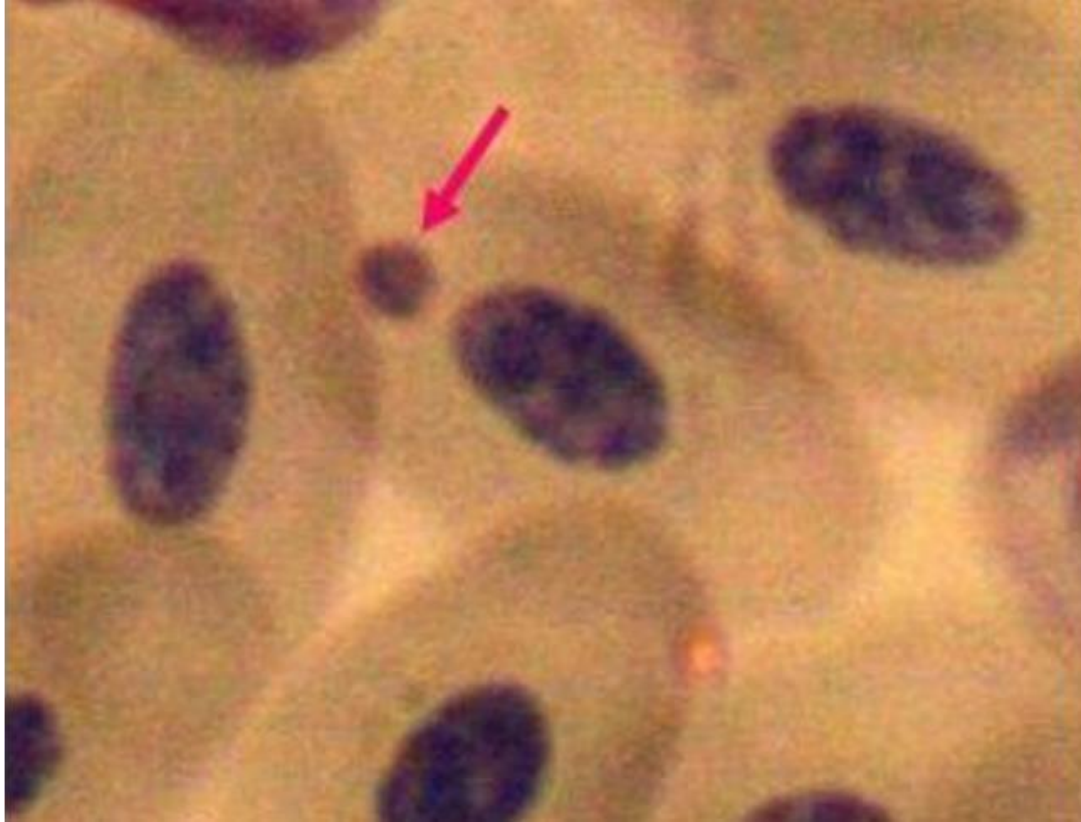
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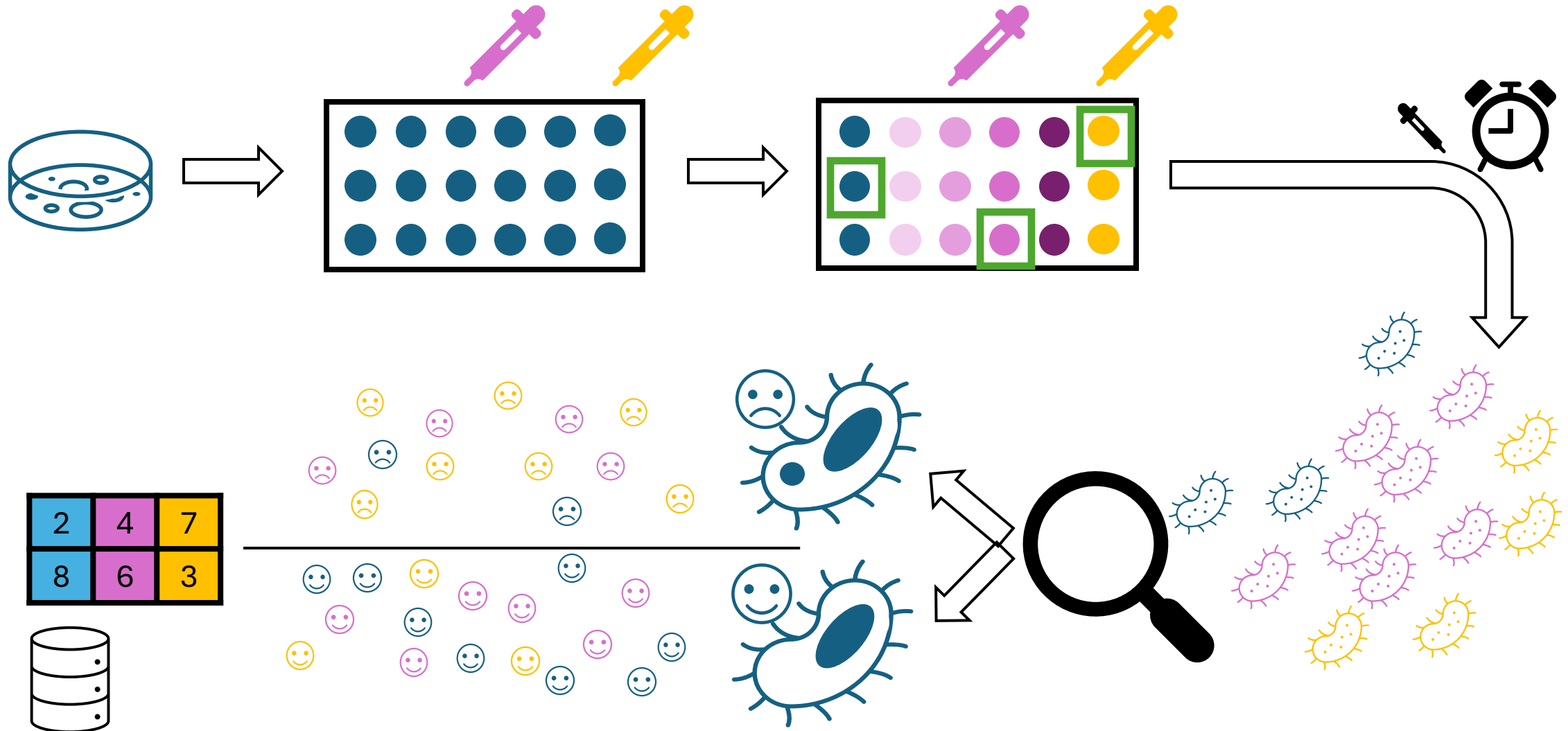
Workshop of the IBS-DR Working Groups 'Non-Clinical Statistics' and 'Bayes Methods', Göttingen, 5/6 December 2024

Micronucleus



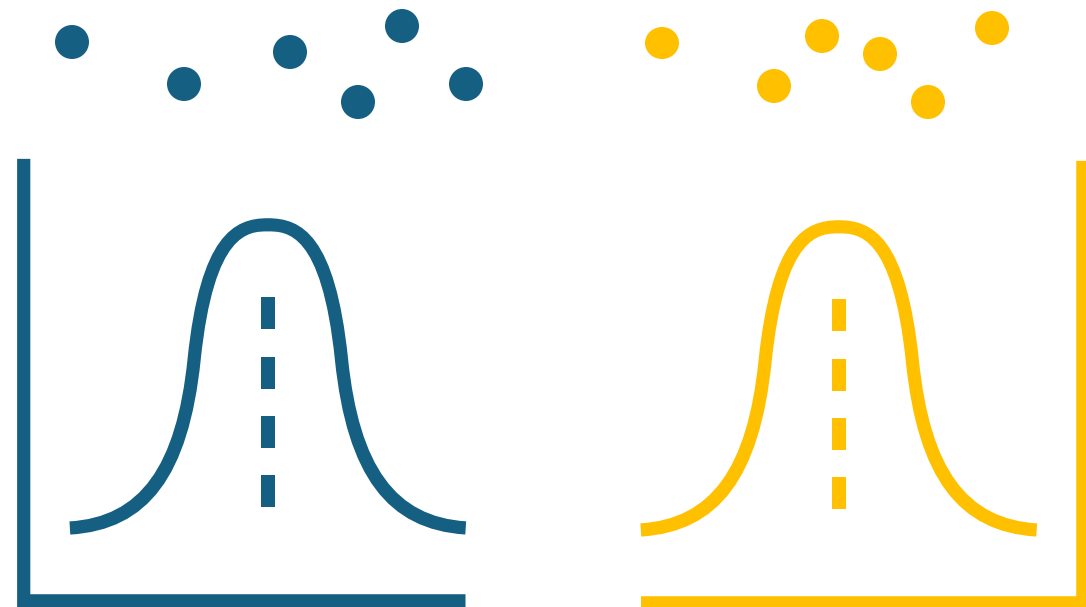
- adverse event during cell division
- small fragment of chromosomes outside new nuclei
- hint to genotoxic conditions

Micronucleus test (MNT) in-vitro



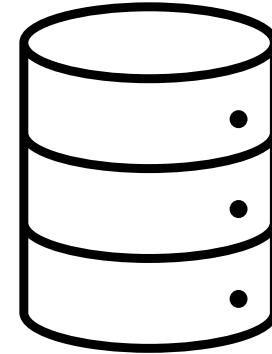
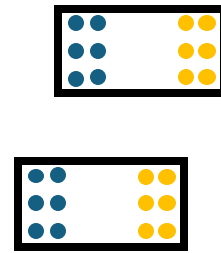
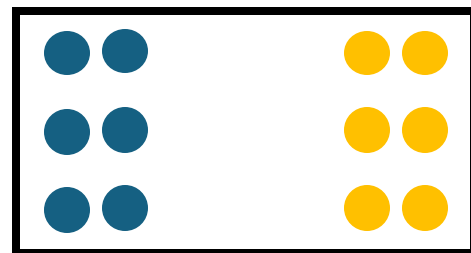
Test assay validation

- ensure validity of results
- OECD Guideline for the Testing of Chemicals 487
- considering **negative** and **positive** control groups
- current experiment's wells' counts compared to historical distributions



Historical control group data

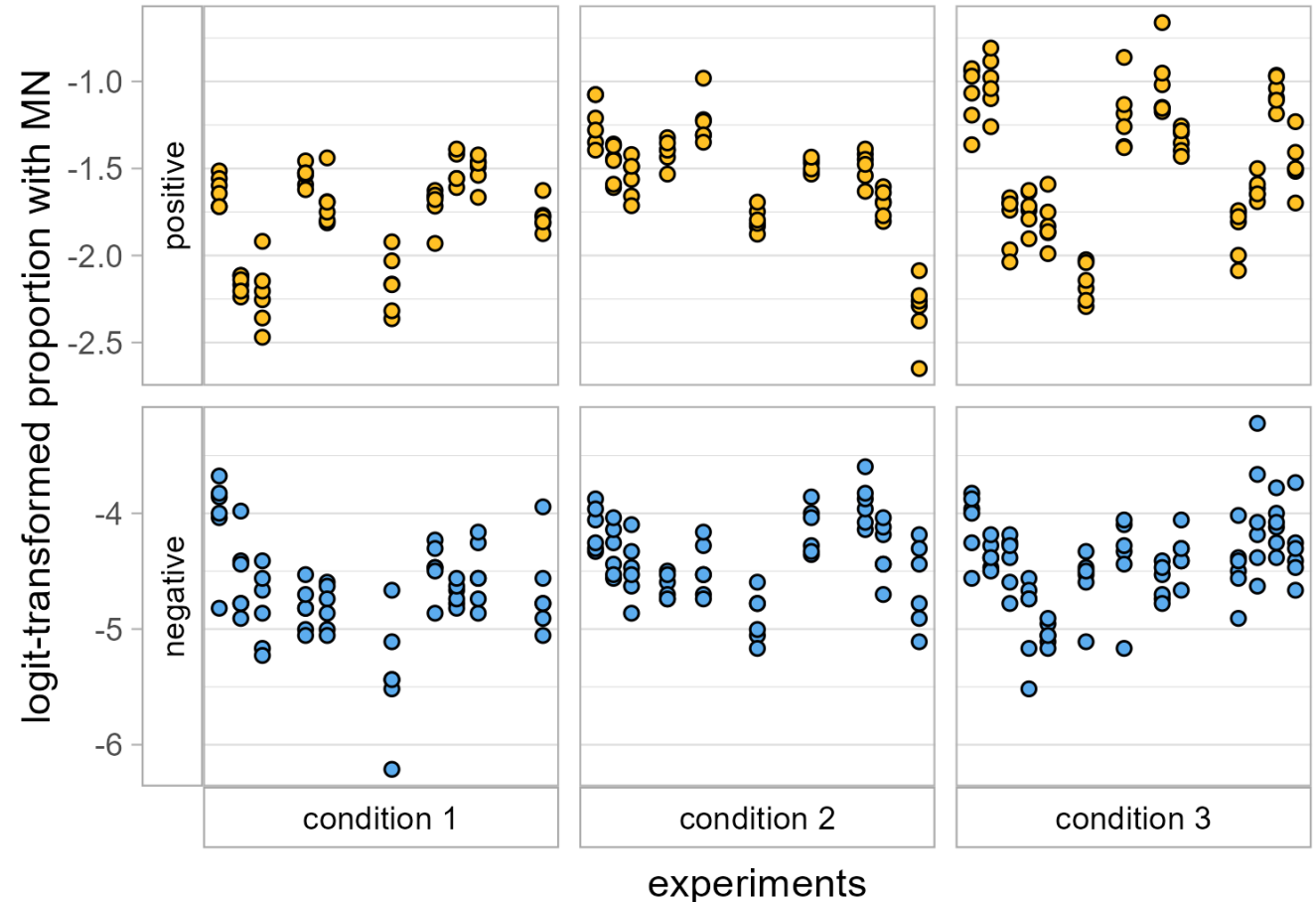
- about $H = 30$ valid historical MNT experiments
- $I = 6$ wells per experiment
- ... for **negative** and **positive** controls
- count data per well:
cells with at least one micronucleus



Endpoint information per well

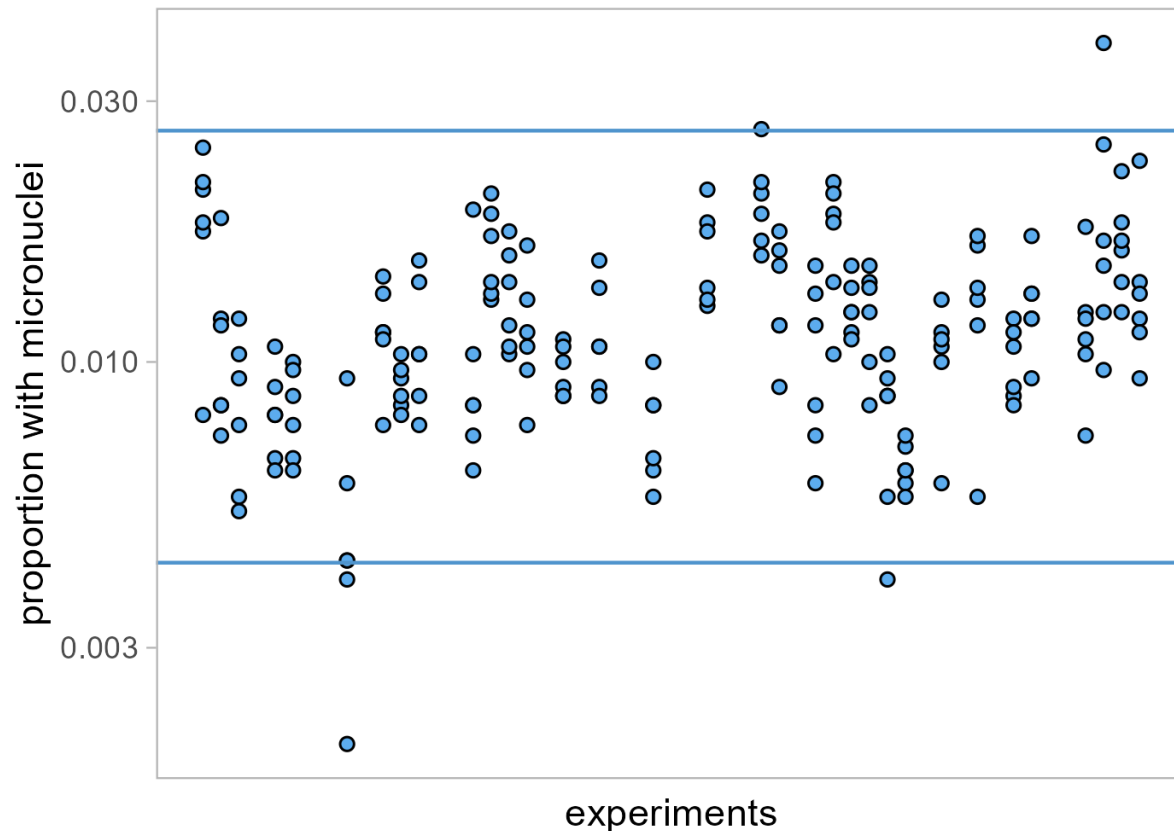
experiment $h = 1, \dots, H$;
well $i = 1, \dots, I$;
 $n = 3000$ cells as target

- **raw:** x_{hi} cells out of n have at least one micronucleus
- **proportional:** $p_{hi} = x_{hi}/n \in (0, 1)$
- **transformed:** $z_{hi} = \log(p_{hi}/(1 - p_{hi})) \in \mathbb{R}$



Prediction intervals

95% prediction interval for ONE well
for negative controls, with 'new data'



- for micronucleus proportion $p_{(H+1)1}$ of ONE well in a future experiment
- directly interpretable on data level
- several model candidates
- evaluation by cross validation, leaving out one historical experiment per run

Conventional models

$x_{hi} \sim \text{Bin}(n, \pi)$ or

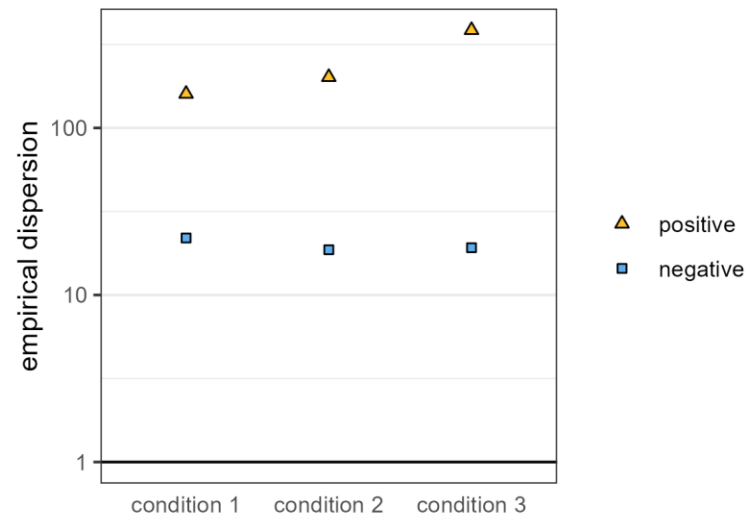
$z_{hi} \sim N(\mu, \sigma^2)$

using all data without experiment information

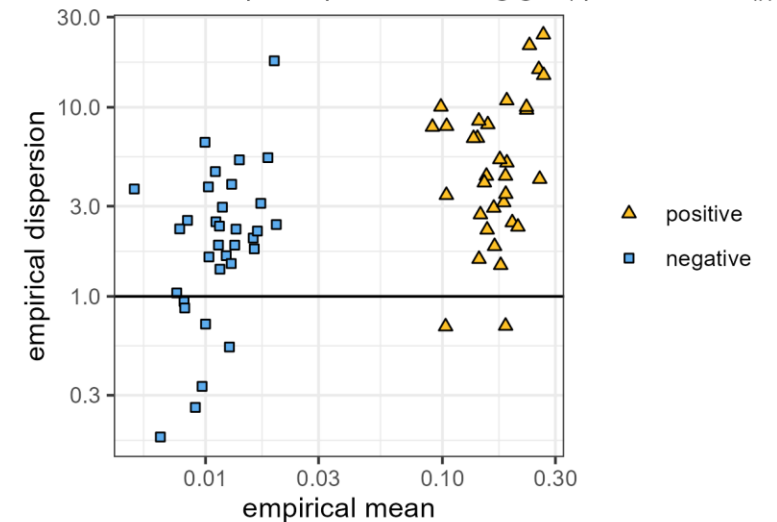
not accounting for

- overdispersion between experiments (random effects of experiments)
- overdispersion within experiment (random effects of wells)

dispersion between experiments
estimated using `glm(quasibinomial())`



dispersion within experiments
estimated per experiment using `glm(quasibinomial())`



Bootstrap-calibrated prediction intervals

- R package `predint`
(Menssen and Schaarschmidt 2022, *Stat Neerl* 76(3);
Menssen et al. 2024, *Pharm Stat* online-first)
- accounting for between-experiment-overdispersion
 - using aggregated count data $X_h = \sum x_{hi}$ on experiment level
 - not accounting for within-experiment-overdispersion
 - predicting total count per experiment

- **beta-binomial:**

$$\pi_h \sim \text{Beta}(a, b)$$

$$X_h \sim \text{Bin}(n \cdot I, \pi_h)$$

- or equivalently (n and I constant) **quasibinomial:**

$$E(X_h) = \pi \cdot n \cdot I$$

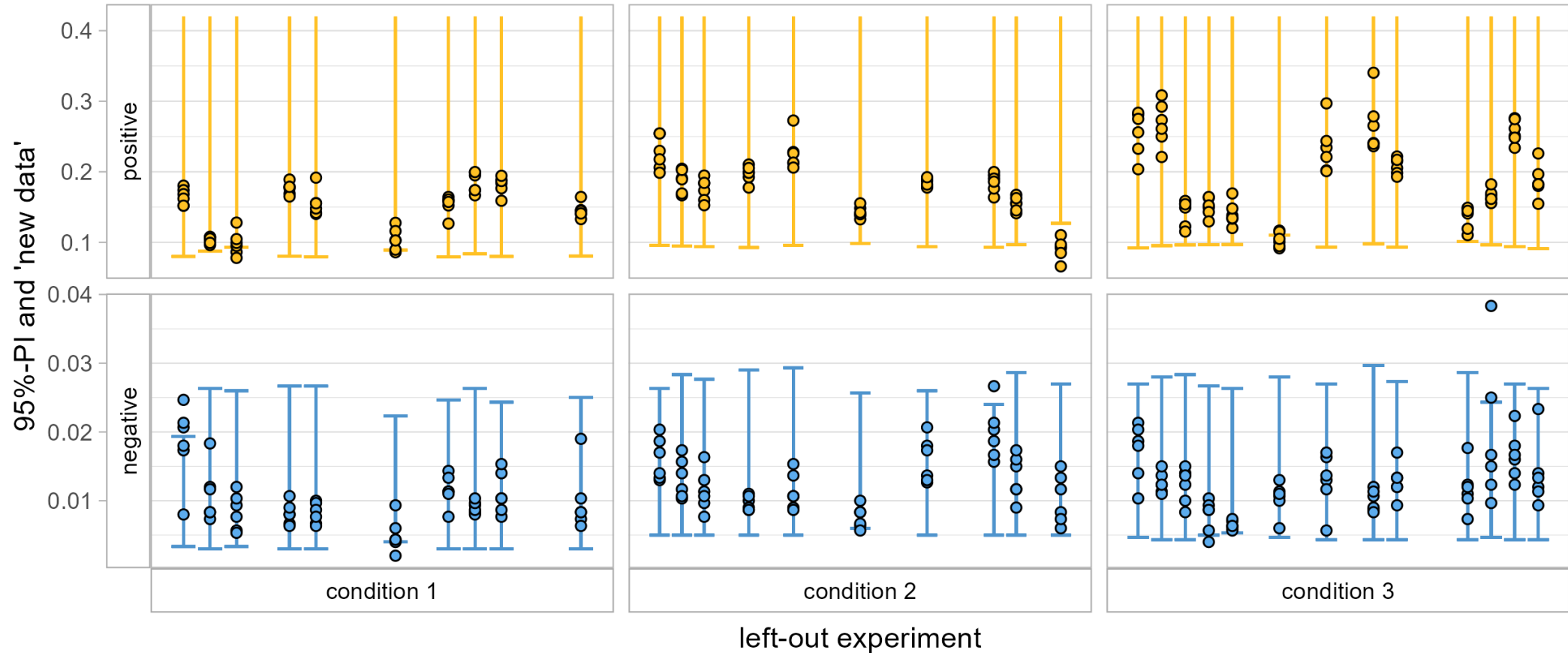
$$\text{Var}(X_h) = \phi \cdot \pi \cdot (1 - \pi) \cdot n \cdot I$$

Bayesian (generalized) random effect models

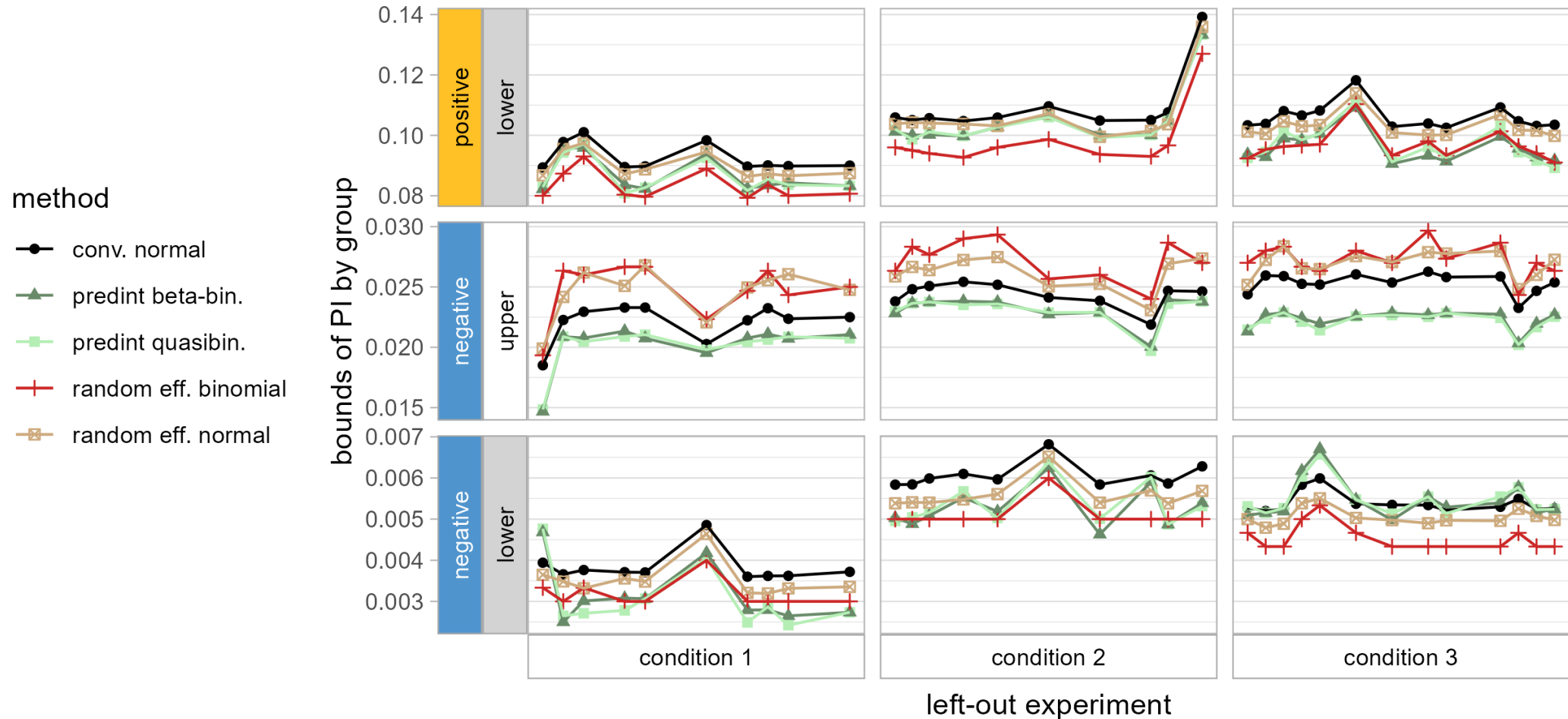
	overdispersed binomial	approximative normal
data	$x_{hi} \sim \text{Bin}(n, \pi_{hi})$	$z_{hi} \sim N(\mu_h, \sigma^2)$
transformation	$\pi_{hi} = \text{logit}^{-1}(\mu_{hi})$ $\mu_{hi} = \alpha + \beta_h + \gamma_{hi}$	$\mu_h = \alpha + \beta_h$
random effects	$\beta_h \sim N(0, \tau^2)$ $\gamma_{hi} \sim N(0, \sigma^2)$	$\beta_h \sim N(0, \tau^2)$
model-parameters	$\alpha \sim (-\infty, +\infty)$ $\tau^2 \sim (0, +\infty)$ $\sigma^2 \sim (0, +\infty)$	$\alpha \sim (-\infty, +\infty)$ $\tau^2 \sim (0, +\infty)$ $\sigma^2 \sim (0, +\infty)$

Cross-validated prediction intervals

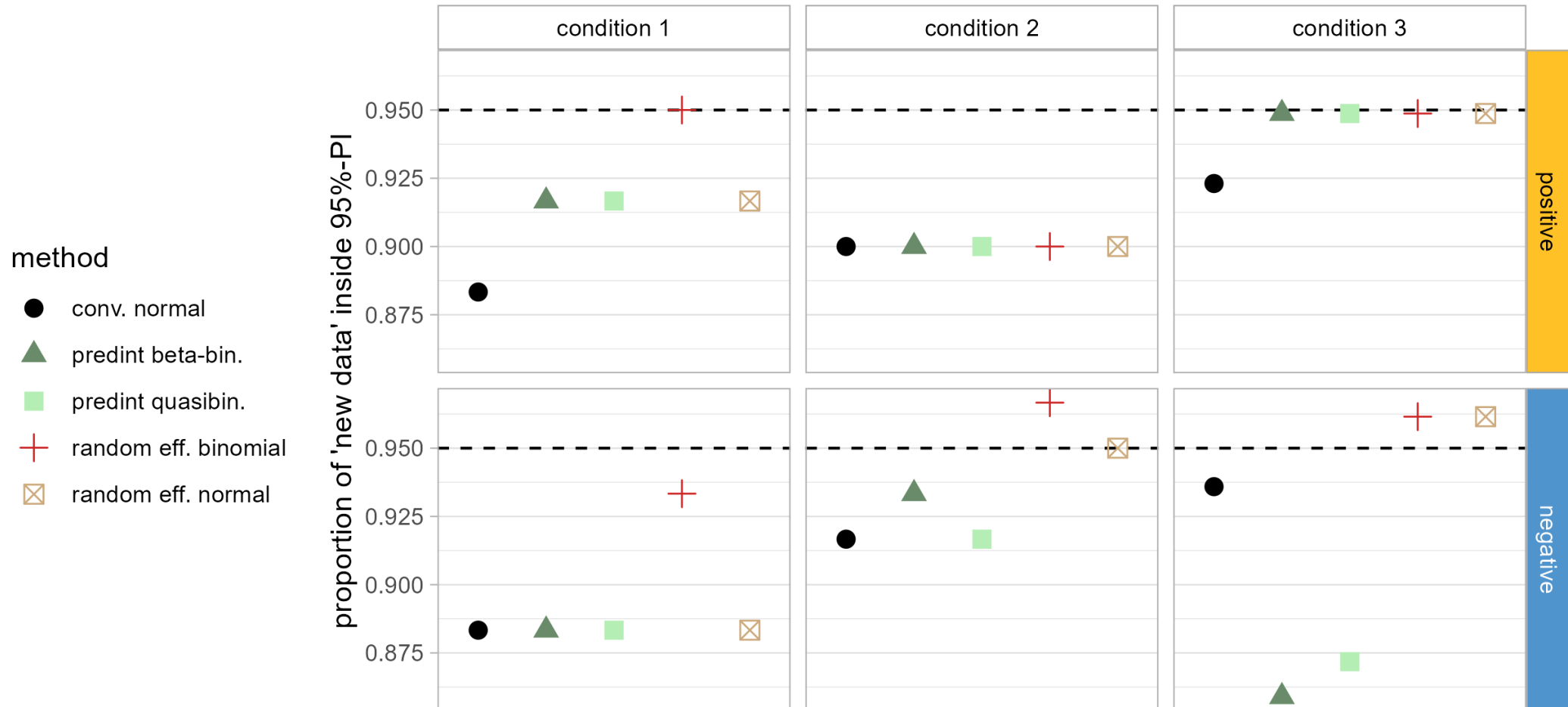
Example: Bayesian overdispersed binomial



Comparison of prediction interval bounds



New data inside interval – overall proportions



Results' summary



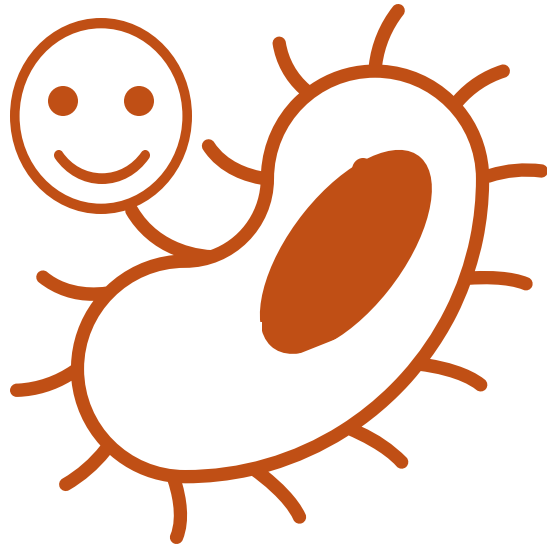
- small differences between methods
- Bayesian models using individual data
 - ... return wider prediction intervals
 - ... have proportion of 'new' well data within 95%-prediction-interval closer to 95%

Perspectives



- joint analyses of negative and positive controls
 - model all data jointly or
 - consider derived data representing the ratio of positives and negatives
- temporal correlation structure between experiments
- more stable results using larger historical database
- simultaneous prediction for all wells of one future experiment

Conclusions



- prediction intervals from historical controls suitable for validating new experiment
- consider both negative and positive controls
- model individual values
 - with experiment random effects
 - with overdispersion

Thank you!

