Statistical philosophy

Jonathan Dushoff, McMaster University

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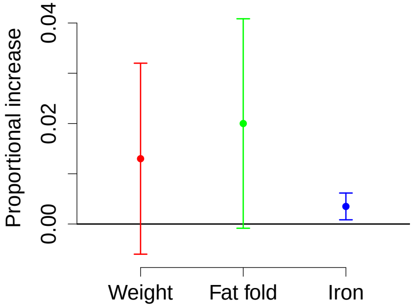

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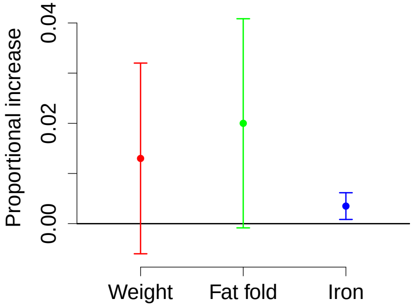

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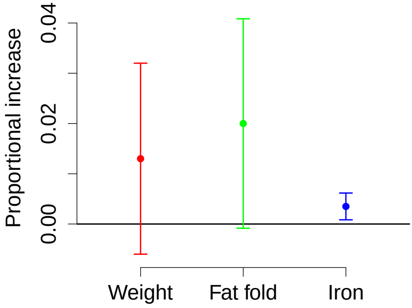

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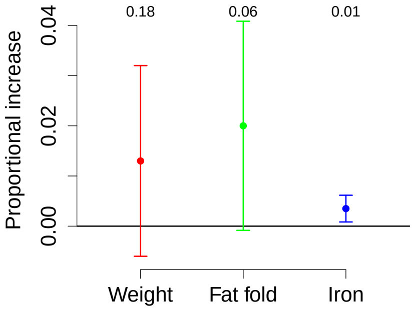

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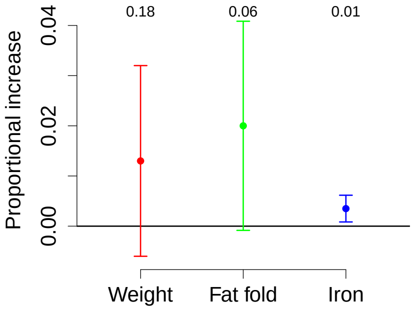

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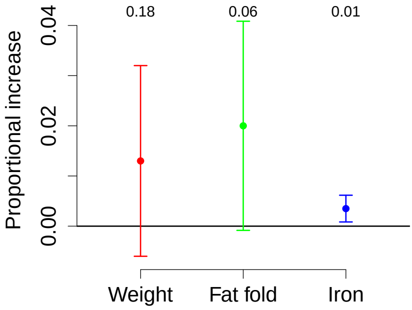

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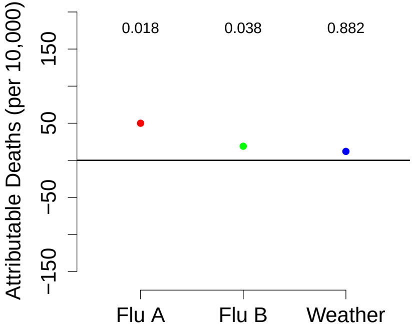

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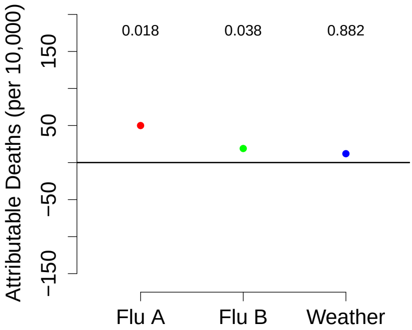

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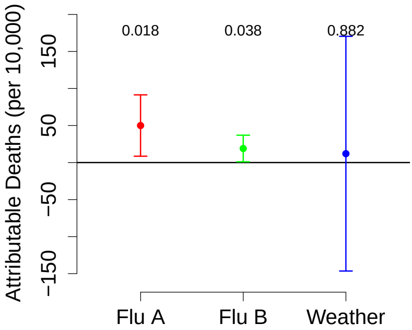

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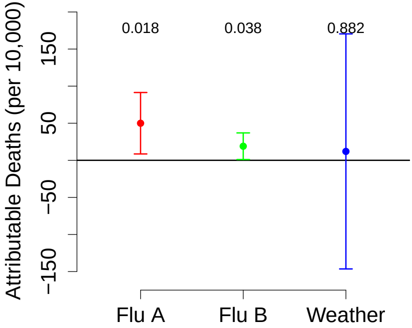

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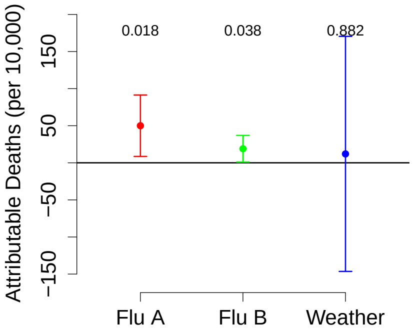

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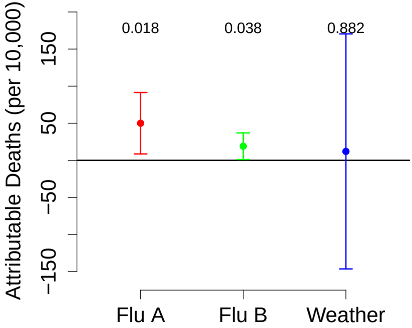

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Statistics and science

Paradigms for inference

Frequentist paradigm

Bayesian paradigm

Conclusion

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- All men are mortal

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WARNING
This respirator helps protect against certain particles. Misuse may result in sickness or death. For proper use, see supervisor or box or call 3M 1-800-247-3941 NIOSH
3M 8210
N95

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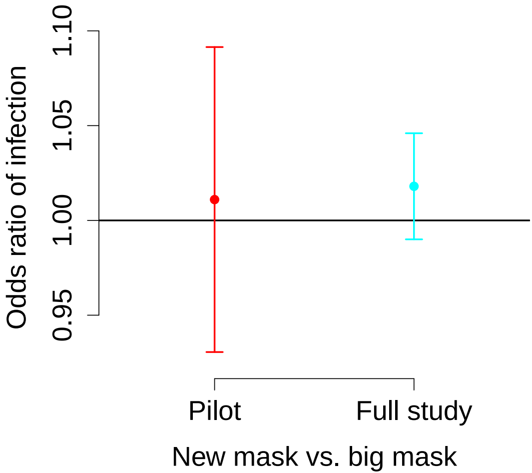

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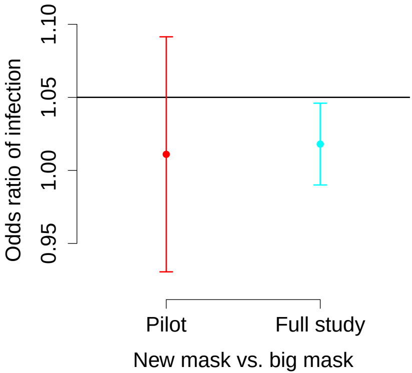

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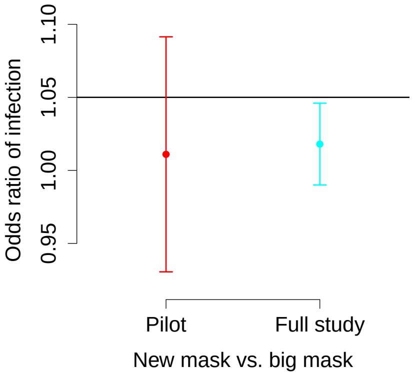

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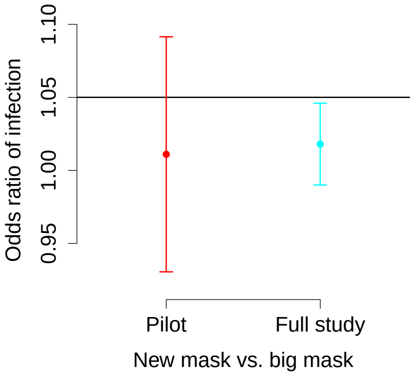

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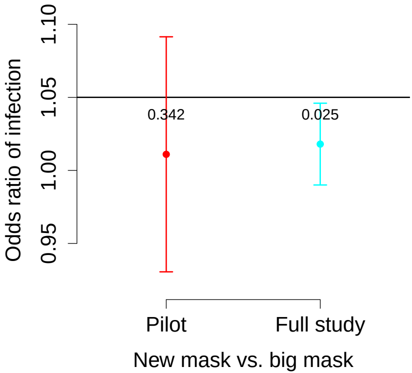

- We can even attach a P value by basing it on the “right” statistic.

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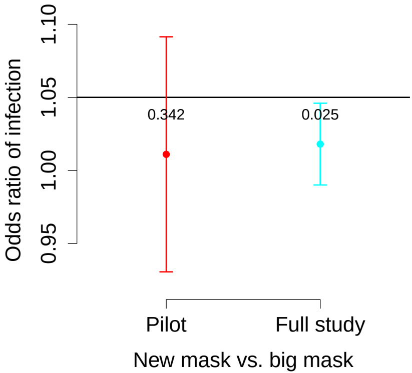

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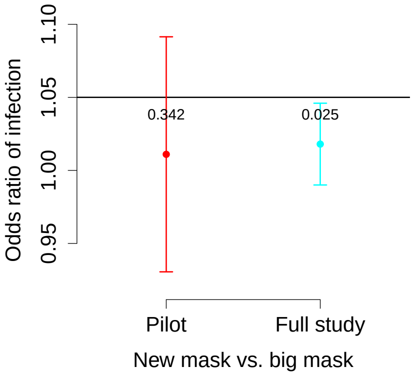

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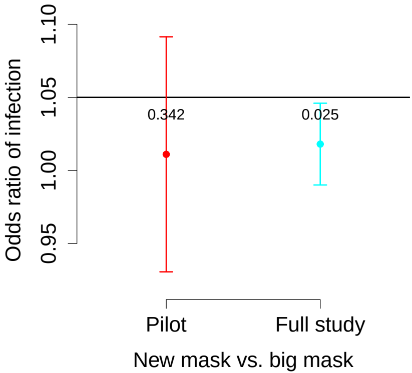

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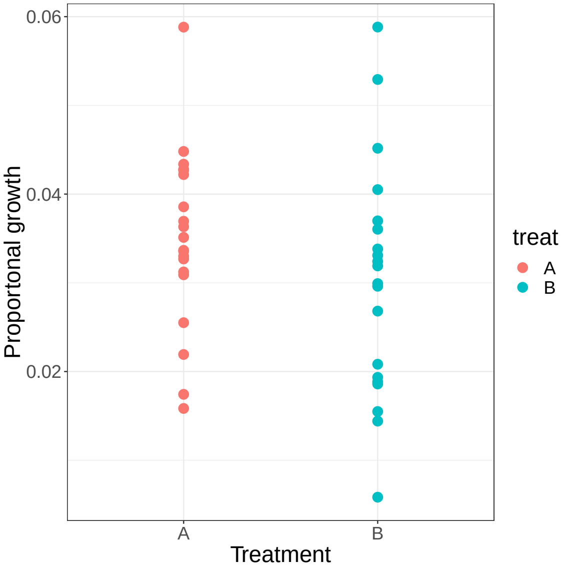

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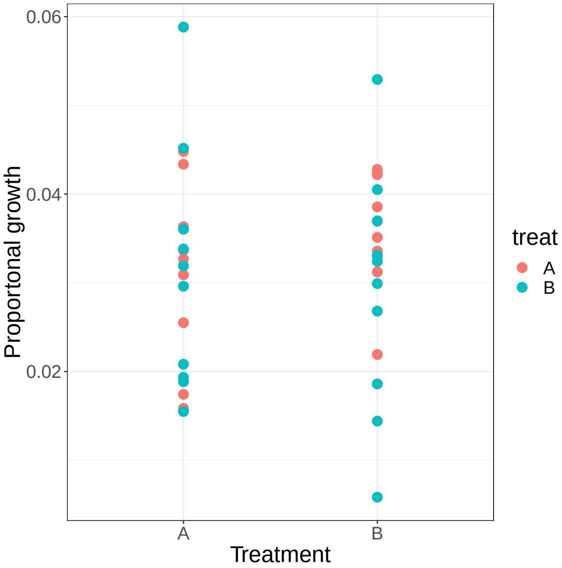

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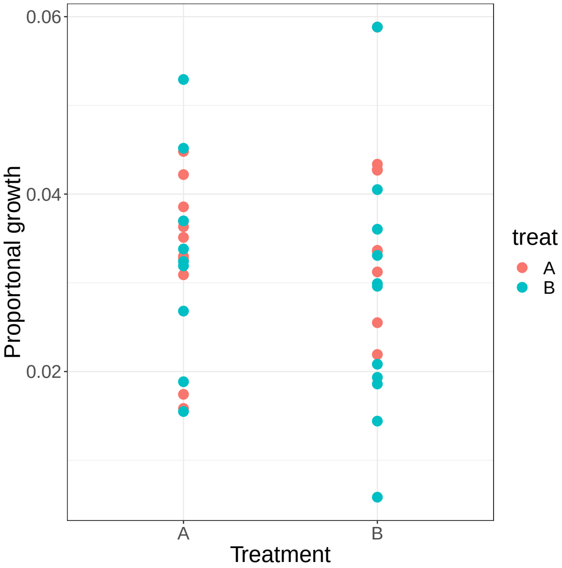

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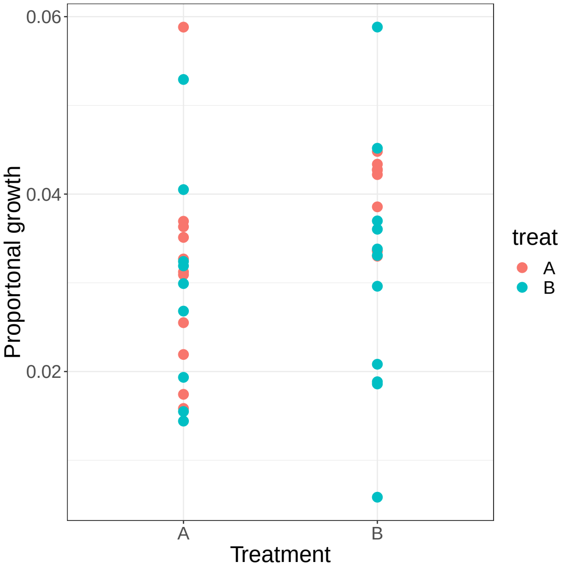

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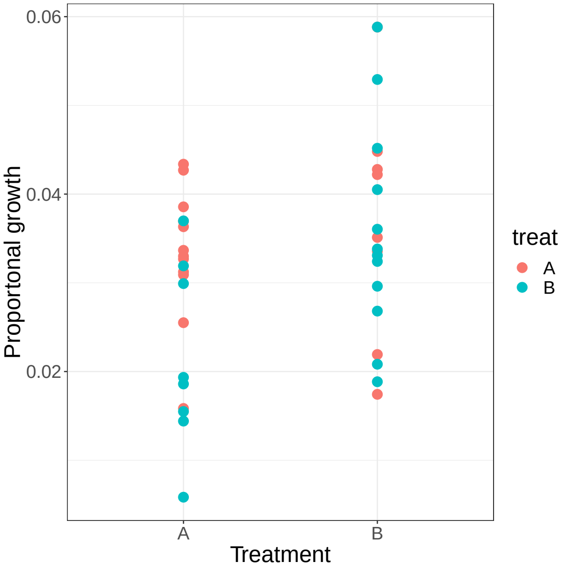

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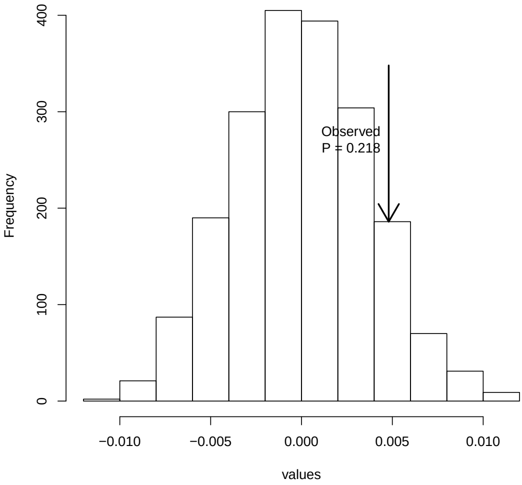

Outline

Statistical inference

- P values and confidence intervals
- Statistics and science

Paradigms for inference

- Frequentist paradigm
- Bayesian paradigm

Conclusion

Bayesian paradigm

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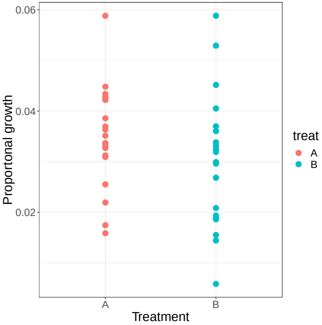

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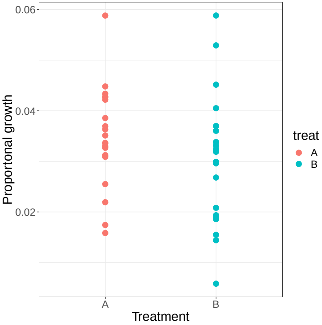

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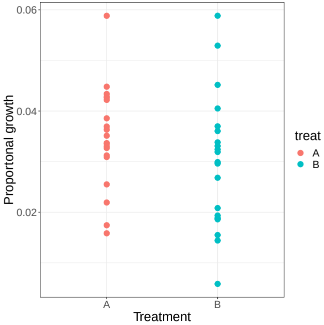

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Tessa Wessels, Faces on a Train

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