Computation infrastructure for teaching Bayesian modeling

Colin Rundel

Univ of Edinburgh
Duke University

Context

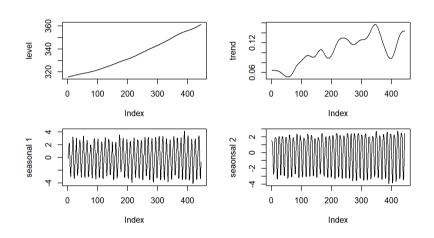
Sta 444 / 644 - Spatiotemporal Modeling

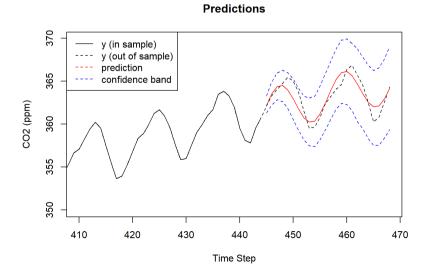
- 4th year undergraduate elective (2nd year MS elective)
- Prereq Sta 360 Bayesian Inference and Modern Statistical Methods
- Weekly labs / problem sessions with TA
- 5 hws + 1 group project over the semester (mathematical, computational, and applied problems)

Learning Outcomes

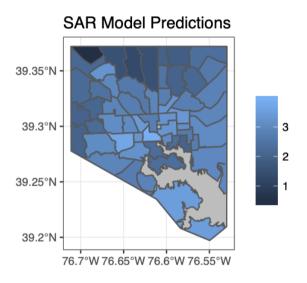
- Modeling methods (lm, glm, ARIMA, GPs, CAR, etc.)
- Model assessment and validation
- Bayesian model implementation (probabilistic programming)

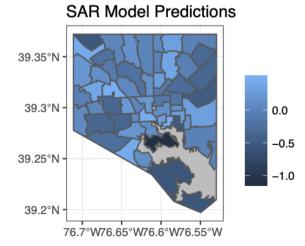
DLM for predicting CO_2





Violent Crime in Baltimore City





Software

- Wide varierty of choices: BUGS, Jags, Stan, etc.
- Some considerations:
 - Generalizability vs. specificity
 - Syntactic complexity
 - Performance
 - Limitations

Computational Complexity and Efficiency

This is often the first course where students engaged with models that cannot be fit "instantly".

- Basics of algorithmic complexity
- Model limitations vs software limitations
- Implementation vs run time

Infrastructure

The platform provided for students matter (labs vs. servers vs. student laptops):

- Configuration / Administration
- Performance
- Workflows

Thank you!



rundel@gmail.com



@rundel



bit.ly/JSM2020_Sta444



stat.duke.edu/~cr173/Sta444_Fa18/