Name: Myisha Hassan
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Paper Title: Inferring Causal Impact Using Bayesian Structural Time-Series Models
Author Names: Kay H. Brodersen, Fabian Gallusser, Jim Koehler, Nicolas Remy And Steven L. Scott
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Open questions for discussion in class:

- The model assumes that the relationship between the treated series and the control series during the pre intervention period holds into the post intervention period. How realistic is this assumption in real world policy or marketing settings where structural breaks are common?
- The method models uncertainty extremely well but computational cost can still become an issue for large scale and high frequency datasets. Are there approximate Bayesian structural time series methods that preserve most of the uncertainty benefits while being cheaper to run?

The topic areas covered by the paper are:

- Causal inference in observational time series settings using Bayesian methods
- Structural time series modeling (state space models, Kalman filtering)
- Counterfactual prediction for estimating causal effects
- Variable selection via spike and slab priors
- Applications to marketing, economics, and policy evaluation

The previous approaches to this problem were:

- Difference in-Differences (DiD) methods, which rely on strong parallel-trend assumptions and don't model uncertainty well
- Synthetic control methods that create a weighted control unit but lack formal Bayesian uncertainty quantification
- Traditional regression based treatment which control comparisons that produce point estimates rather than full posterior distributions
- Propensity score based approaches that help balance groups but don't handle time series structure effectively

Outline the basic new approach or approaches to this problem:

- Proposes a Bayesian structural time series model to generate a counterfactual trajectory for what would have happened without the intervention
- Combines 3 sources of information which are:
    - The target time series before the intervention
    - A set of control time series that were not exposed to the intervention
    - Prior distributions over model components
- Uses spike and slab priors for automatic predictor selection and modeling averaging
- Performs MCMC to estimate the posterior distribution of the counterfactual, producing a full distribution of casual effects rather than a single number

- Allows uncertainty to accumulate naturally as predictions move further into the post intervention window

Critical assumptions made include:

- Control variables are <u>not themselves affected</u> by the intervention
- The relationship between treated and control time series remains stable from pre to post intervention
- Observational time series contain no unmodeled structural breaks that would break the predictive relationship
- Priors reasonably reflect domain knowledge or provide enough regularization
- The MCMC sampling converges appropriately and the model is sufficiently identified

The performance of the techniques discussed in the paper was measured in what manner:

- Synthetic data experiments were used to validate whether the method could recover known impacts
- Posterior predictive checks assessed how well the model captured pre intervention dynamics
- Width and behavior of credible intervals were examined to demonstrate uncertainty propagation
- Real world evaluation: the method was compared against results from an actual randomized experiment using a two stage linear model, showing that the Bayesian model produced comparable causal estimates
- Visual comparison between observed post intervention data and posterior predictive counterfactual estimates

What background techniques are used in the paper that you are not familiar with:

- Spike and slab priors for Bayesian variable selection
- Kalman filtering and diffusion regression state space models
- Bayesian synthetic control construction
- Posterior predictive simulation for causal impact curves

The following terms were defined:

- Causal Impact: The difference between observed outcomes and the posterior predictive counterfactual distribution
- Counterfactual Time Series: Estimated trajectory of the treated unit had the intervention not occurred
- Synthetic Control: A weighted combination of control series used to model the target series' counterfactual behavior
- Spike and Slab Prior: A Bayesian prior that allows variables to be "on" or "off," used for predictor selection
- Posterior Predictive Interval: Uncertainty range for future or counterfactual predictions under the Bayesian model
- Structural Time Series Model: A state space model decomposed into trend, seasonality, regression components, etc.

I rate and justify the value of this paper as:
9/10. This paper does a great job showing how Bayesian methods can solve a real limitation in causal inference for observational time series data: the lack of a proper counterfactual and the need for uncertainty quantification. I especially liked how the authors used a Bayesian structural time series model to create a full posterior distribution over the counterfactual instead of just giving a point estimate. The spike and slab variable selection made the method feel flexible and data driven, and the comparison to results from an actual randomized experiment made the approach feel trustworthy. The synthetic example was especially helpful for understanding how the method behaves when the "true" effect is known, and the visualizations made the results intuitive. The only reason I didn't give it a full 10/10 is that some of the state space modeling details (like the Kalman filter components) were a bit dense and required more background than the paper provided. Still, overall it's a strong and very practical demonstration of how Bayesian modeling can improve causal inference in real world settings.