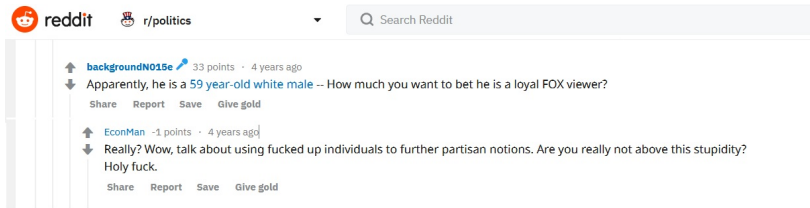


Machine Learning Predictions as Regression Covariates

Matt Tyler Christian Fong

March 1, 2019

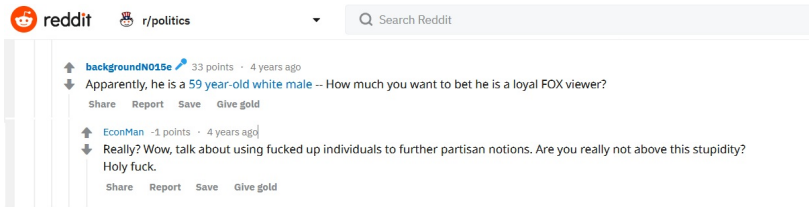
Studying Uncivil Political Dialogue



The screenshot shows a Reddit post from the subreddit r/politics. The post is by user 'backgroundN015e' and has 33 points. The title is 'Apparently, he is a 59 year-old white male -- How much you want to bet he is a loyal FOX viewer?'. Below the title are options to 'Share', 'Report', 'Save', and 'Give gold'. A reply by user 'EconMan' has -1 points and says 'Really? Wow, talk about using fucked up individuals to further partisan notions. Are you really not above this stupidity? Holy fuck.' Below the reply are options to 'Share', 'Report', 'Save', and 'Give gold'.

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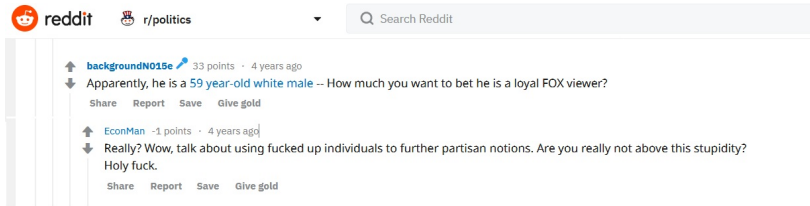
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The screenshot shows a Reddit interface for the subreddit r/politics. At the top, there is a search bar with the text "Search Reddit". Below the search bar, the subreddit name "r/politics" is visible. The main content shows a post by user "backgroundN015e" with 33 points and 4 years ago. The post text is "Apparently, he is a 59 year-old white male -- How much you want to bet he is a loyal FOX viewer?". Below the post, there are two comments. The first comment is by user "EconMan" with -1 points and 4 years ago, containing the text "Really? Wow, talk about using fucked up individuals to further partisan notions. Are you really not above this stupidity? Holy fuck." The second comment is by user "backgroundN015e" with 33 points and 4 years ago, containing the text "Apparently, he is a 59 year-old white male -- How much you want to bet he is a loyal FOX viewer?".

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Anastosopoulos et al. (2017)
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- These are substantial biases that limit hypothesis tests of $b = 0$

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 - (Asymptotically) more efficient than just using data where x_1 is coded

Our Method in Three Steps

- ① Divide the Coded Data into Training and Validation Subsets

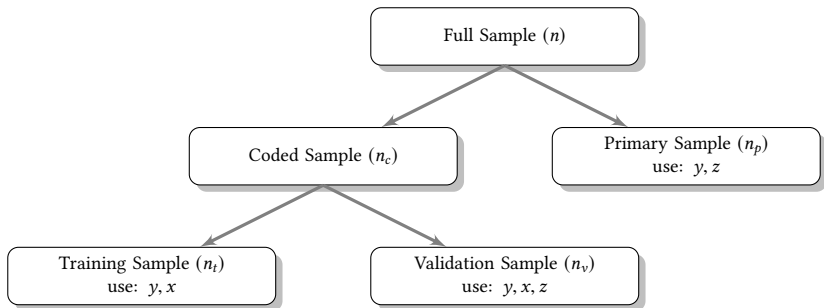
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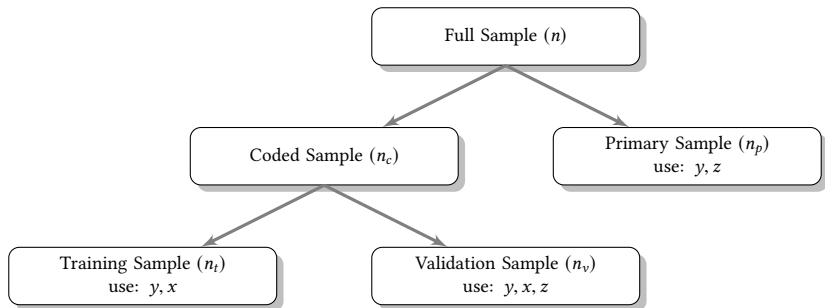
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Step 1: Divide the Coded Data into Training and Validation Subsets



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↪ Training sample to fit z -algorithm, but then hide its z values from Steps 2 & 3 to avoid overfitting bias

Step 2: First-Stage Regression

- We can always find $\Lambda_0 = [\lambda_{10} \quad \lambda_{20} \quad \cdots]$ so that

$$x_1 = z' \lambda_{10} + \eta_1$$

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- Compactly write $x' = z' \Lambda_0 + \eta'$ with $E(z\eta') = 0$

Step 2: First-Stage Regression on Validation Sample

- Given Exclusion Restriction, plug in $z'\Lambda_0$ for x' :

$$y = z'\Lambda_0\beta_0 + \bar{\epsilon}, \quad E(\Lambda_0'z\bar{\epsilon}) = 0$$

\implies we can use 2SLS on the uncoded data to estimate β_0

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- e.g.,

$$\hat{\lambda}_k = \left(\sum_{i=1}^n v_i z_i z_i' \right)^{-1} \left(\sum_{i=1}^n v_i z_i x_{ik} \right) \quad (1)$$

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- 2SLS on the primary & validation samples:

$$\hat{\beta}_2 \text{ such that } g_2(\hat{\beta}_2) = 0$$

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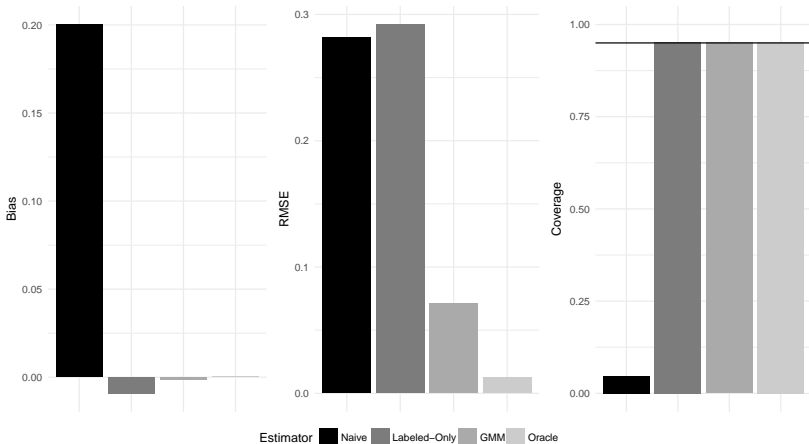
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Data-Based Simulation: GMM is Equal to Coding 16 Times More Posts



Applying the GMM Estimator

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+ [redacted] 6 points · 3 years ago
+ Slow your roll bro.
  You have no idea if the plane was unpowered or what attitude it came down at. It could have been a power dive directly
  into a cliff face.
  Calling everyone a [redacted] when you're the one using confusing language isn't helping anything.
  Show · Report · Save · Give gold

+ [redacted] 11 points · 3 years ago
+ If you can't connect the difference between 'passenger plane' and 'jet' when I say it, knowing what sort of plane has
  crashed and what sort of plane is in the video, you are in fact a [redacted]. The report I've read says the plane was
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  Show · Report · Save · Give gold

+ [redacted] 2 points · 3 years ago
+ Wow look at this [redacted]
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+ [redacted] 4 points · 3 years ago
+ You want a medal for that bravery?
  Show · Report · Save · Give gold

+ [redacted] 1 point · 3 years ago
+ As long as the cost of P&P isn't too dear when you send it to me.
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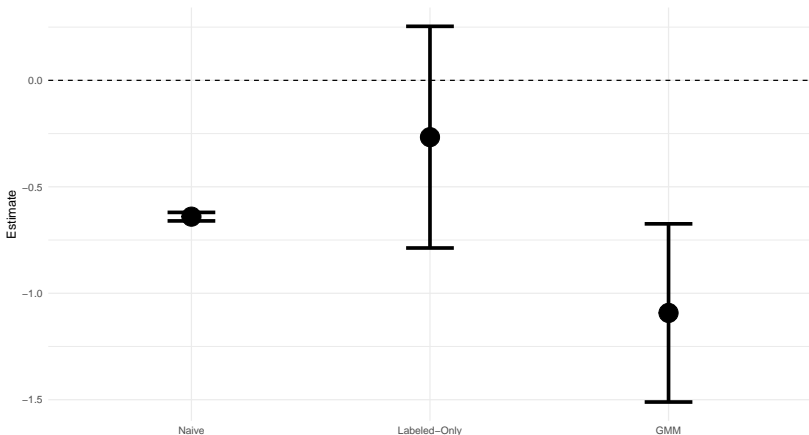
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- 5,000 most common words + LASSO $\implies z$

GMM Corrects for Naive Estimator's Attenuation Bias



GMM: uncivil posts on average have ≈ 1.1 (0.2) lower score

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- Nonparametric methods that do not lean on ER (Chen, Hong, & Tamer 2005) are not RMSE-competitive in realistic scenarios (appendix)

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Summary

- Highlighted an algorithmic theme in recent empirical work across subdisciplines of political science
- Many practitioners are plugging-in algorithmic predictions or using ad-hoc adjustments
- We provide a robust solution that does not depend on classical measurement error assumptions
- No functional form or homoskedasticity assumptions
- More efficient than just using hand-coded data!