Presentation Notes

Date: November 24, 2024

General Presentation framework:

- What is the topic, why does it matter for official statistics?
- Definitions and key methods explained simply
- examples
- contributions
- flowcharts, graphs, tables
- conclusion

1. Section 1: Estimation of the generalization error and its uncertainty

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2. Section 2: Interpretable machine learning

(Same format as above) "Would you trust an ML model if you couldn't explain its decision?"

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3. Section 3: Machine learning for complex sample designs

(Same format as above)

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4. Section 4: Quantitative methods for uncertainty quantification

(Same format as above)

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5. Section 5 (MLops): Machine learning operations and reproducibility in official statistics

Key POints:

- what? is mlops
- Why? MLOps ensures that ML systems used in official statistics are reusable, transparent and scalable

- also why? MLOps practices build trust in ML systems for official statistics by ensuring transparency and reproducibility
- concepts? version control for data and models, CI/CD pipeline

Visual Ideas:

⋆ MLOps pipeline chart

⋆ explaining each step with a video or a real time example (also really depends on how familiar they are with this)

⋆ example of dealing with bias (the formula)

⋆ visually showing the way ahead?

⋆ the connection between Interpretability and fairness of ML

⋆ A messy vs a clean process (good way to understand the importance better)

⋆ also like what you have now + the additions we are trying to get

⋆ results first and then the pipeline description

⋆ the git repository

⋆ talking about mlops best practices to be sure of the internal working standards and handling possible future problems (maybe a document for this would be enough though)

⋆ extensions, couldera, data leaks (not sure how much depth to go into these)

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6. Section 6: Fairness and Bias Auditing

Key Points:

- techinical + social and societal challenges of ML in public sector
- what are the problems? ans: shifts in decision making responsibility and immense technical stability
- protected attributes
- measurement errors can also affect model training
- group, subgroup and individual fairness (concepts, and challenge)
- prediction and decision step (talking about how crucial the prediction step in official statistics is)
- The fairness of ADM systems starts way before decisions are made. Every step in the data pipeline - from designing surveys to cleaning and processing data - contributes to the fairness (or unfairness) of the final sustem

- Some effects may have bigger impact than others
- Two steps of ADM where prediction step directly affects the decision step
- integrating fairness aspects into existing quality criterion (contributions)
- the way ahead with the possible new opportunities (contribution)

Visual Ideas:

- ⋆ Example: Bias in a loan approval system
- ⋆ Data collection -¿ Cleaning -¿ Training -¿ Prediction -¿ Decision, with bias sources highlighted at each stage.
- ⋆ example of dealing with bias (the formula)
- ⋆ visually showing the way ahead?
- ⋆ the connection between Interpretability and fairness of ML

Contributions

C1: we propose an extension of the “Quality Framework for Statistical Algorithms” (QF4SA; Yung et al. 2022), with which fairness considerations can be embedded in existing quality guidelines

C2: suggesting, Data from official statistics can be used as benchmark data for fairness evaluations, both in comparison to other data and for ML models themselves.

- are we talking to different sets of people, or is it one audience
- what is their familirarity wiht the existing mehtods
- how much stat/math/ml/code/python/r/mlops do they know? even like github?
- atleast for the coded parts, maybe a document with the tutorial would be very benefical. or a recorded one because this might possibly be a big struggle
- questions: what? why? what has been working so far (objective 1) ? how are we helping this to make it better (objective 2)? how to integrate this all and go ahead?
- visual diagrams of the pipeline or the problem + real world synthetic official statistics examples
- not go too theoretical, but explain it more visually
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