

Automated Assessment of Residual Plots with Computer Vision Models

Response to reviewers

2026-01-12

We thank the editor and the reviewer for their constructive comments that have improved this paper. We have addressed all comments, colored in **purple**. In addition, we also include an annotated version of the paper (`diff.pdf`) with the difference between the original and revised versions produced using `latexdiff`.

Reviewer

General Comments

The idea of the paper seems interesting: using computer vision to help identify residual plots which indicates model violation. For any computer vision task, the input is clearly the image. However, there should be a clear definition of the outcome variable that the algorithm wants to predict from images. From the current draft of this paper, it is unclear that what is the outcome variable that the computer vision is learning from the residual plots, how the training datasets are created for computer vision learning, and how the performance of the computer vision algorithm is assessed. Please see my detailed comments in items 10, 12,13. I suggest the authors make these basic setups explicitly defined from the very beginning of the article.

Specific Comments

1. p3, l9: What is “the lineup protocol”?

The lineup protocol was first introduced in Buja XXXX and used across a number of literatures to assess statistical graphics. We explain in XXXX.

2. missing references: Loy and Hofmann (2013; 2014; 2015)

We are unsure what this refers to as the reference is shown in our submission.

3. p8 l16: Why do we need to replace it by a full-rank covariance matrix?

4. eq (2), typically KL is specified by $KL(p \parallel q)$ due to asymmetry

We have added modified D_{KL} to $D_{KL}(p||q)$, thank you.

5. p9 l 53: to solve eq 2: using “evaluate” for “solve” is better

We have modified “solve” to “evaluate”, thank you.

6. p19 l30: What is “the data generating process”? We don’t know the true distribution of y .

7. p12, sec 5.1: this sounds like a standard simulation of the sampling distribution of \hat{D} in traditional statistics.

8. p13, Sec 5.2: How do you do bootstrapping? We need to know the distribution of \hat{D} under the null. However, the given observed data y may not come from the null.

9. Tbl1: it is unclear what this table is measuring. What is the R^2 measuring? What’s the response and what is the predictors?

10. Section 7 and 8: In computing \hat{D} , you need a P and Q for each targeted model violation. Is your computer vision learning algorithm targeted a particular model departure, eg, non-linearity or heteroskedasticity? What is your P and Q in generating the training data of \hat{D} and residual plots for computer vision learning? However, your results also show your performance for different kinds of model violations. This is confusing. You need to specify clearly what is the “true” \hat{D} and what the “predicted \hat{D} ” using computer vision in generating training data of \hat{D} and residual plots.

11. There is no numbering for your equations.

We are again unsure what this refers to as the equation numbering is shown in our submission and the reviewer makes reference to equation numbers above.