Advances in Artificial Intelligence for Data Visualization: Automated Reading of Residual Plots with Computer Vision

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1 Overview of the thesis

1.1 Background and motivation

Model diagnostics play a critical role in evaluating the accuracy and validity of a statistical model. They enable the assessment of the model's assumptions, detection of outliers, evaluation of how well the model fits the data, and identification of possible approaches to improve the model's performance.

When conducting model diagnostics, despite the availability of numeric summaries endorsed by finite or asymptotic properties, graphical representations of data are often preferred or required by data analysts. The preference for visual diagnostics is attributed to its intuitive nature and the possibility of discovering unexpected abstract and unquantifiable insights. In the context of regression diagnostics, a common practice is to plot residuals against fitted values, which serves as a starting point for evaluating the adequacy of the fit and verifying the underlying assumptions. Other visualization techniques such as histograms, Q-Q plots and box plots can be used to identify potential issues with assumptions made about the data, such as linearity, normality, or homoscedasticity.

Recently, a novel statistical inferential framework known as visual inference (Buja et al. 2009) has been developed, which relies on the use of graphical representations of data. The visual inference approach makes use of the natural capability of the human visual system to identify patterns and deviations from expected patterns. It provides a more comprehensible way of interpreting data and conducting hypothesis testing compared to conventional statistical testing.

Practically, visual inference is conducted via the lineup protocol. The protocol is inspired by the police lineup technique employed in eyewitness identification of criminal suspects. It comprises m randomly positioned plots, where one of them represents the data plot, while the remaining $m-1$ plots represent the null plots with the same graphical structure, except that the data has been replaced with data consistent with the null hypothesis H_0. An example lineup is provided in Figure 1. To compute the p-value of the visual test, the lineup will be independently presented to a number of participants, asking them to pick the most different plot. Under H_0, the data plot is expected to be indistinguishable from the null plots, and the probability of correctly identifying the data plot by an observer is $1/m$. If a large number of participants correctly identify the data plot, the corresponding p-value will be small, indicating strong evidence against H_0.

This method has gained increasing traction in recent years and has already been integrated into data analysis of various topics, such as diagnostics of hierarchical linear models (Loy and Hofmann 2013), geographical research (Widen et al. 2016) and forensic examinations (Krishnan and Hofmann 2021).
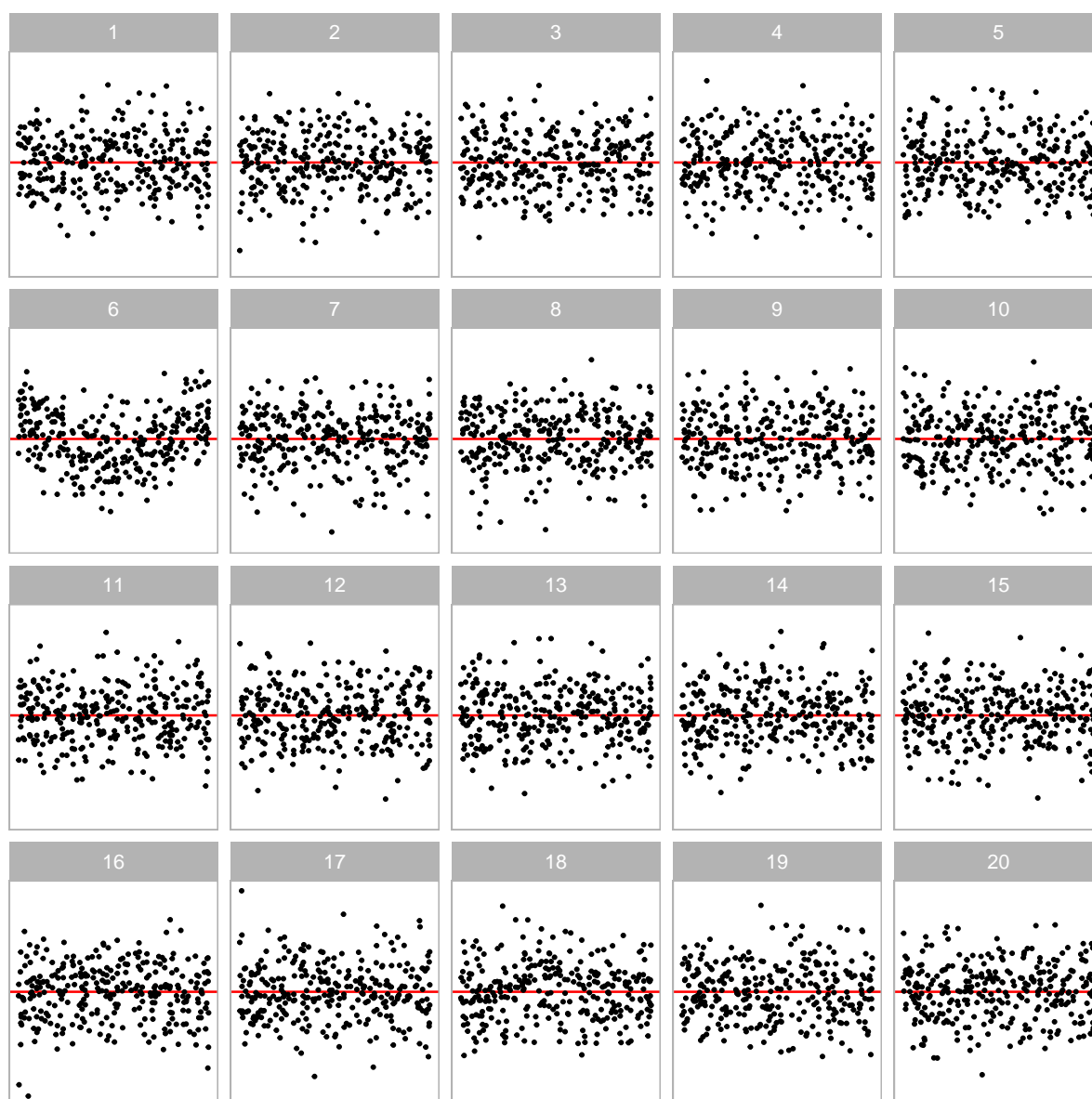
Figure 1: *Visual testing is conducted using a lineup, as in the example here. The residual plot computed from the observed data (plot $2^2 + 2$, exhibiting non-linearity) is embedded among 19 null plots, where the residuals are simulated from a standard error model. Computing the p-value requires that the lineup be examined by a number of human judges, each asked to select the most different plot. A small p-value would result from a substantial number selecting plot $2^2 + 2$.*

With the advent of sophisticated visualization techniques and tools, visual inference has the potential to provide an innovative alternative to traditional statistical approaches and enabling more effective communication of model findings.

The reliance of human assessment is a fundamental aspect of visual tests, but it may restrict its widespread usage. The lineup protocol is unsuitable for large-scale applications, due to its high labor costs and time requirements. Moreover, it presents significant usability issues for individuals with visual impairments, resulting in reduced accessibility.

Modern computer vision models offer a promising solution to this challenge. As a subfield of AI, computer vision with its modern deep learning architectures has successfully resolved numerous critical problems in automation. The development of the convolutional neural network (CNN) by Fukushima and Miyake (1982) was inspired by the vision processing in living organisms. The modern computer vision model typically utilizes deep neural networks with convolutional layers, which leverage the hierarchical pattern in data and provide regularized versions of fully-connected layers. This approach downscales and transforms images by summarizing information in a small space. Numerous studies have shown that it can effectively tackle vision tasks, such as image recognition (Rawat and Wang 2017), computer-aided diagnosis (Lee and Chen 2015), pedestrian detection (Brunetti et al. 2018), and facial recognition (Emami and Suciu 2012).

Utilizing computer vision models in reading data plot is not a common choice. Nevertheless, certain fields have adopted this idea by applying computer vision models in reading recurrence plots for time series regression (Ojeda, Solano, and Peramo 2020), time series classification (Chu et al. 2019; Hailesilassie 2019; Hatami, Gavet, and Debayle 2018; Zhang et al. 2020), anomaly detection (Chen, Su, and Yang 2020), and pairwise causality analysis (Singh et al. 2017). However, the assessment of lineups with computer vision models is a relatively novel area of study.

1.2   Research questions

The main objective of this research is to construct an automatic visual inference system capable of conducting visual tests on a large scale in the domain of regression diagnostics. The study will concentrate on three specific projects, namely

1. Exploring the application of visual inference in regression diagnostics and comparing it with conventional hypothesis tests.
2. Designing an automated visual inference system to assess lineups of residual plots of classical normal linear regression model.
3. Deploying the automatic visual inference system as an online application and publishing the relevant open-source software.

1.3   Current research outcomes

In order to examine the potential applicability of integrating visual inference techniques into regression diagnostics, a pilot study was conducted in the first year with the participation of 64 individuals, which was followed by a formal study involving 443 participants in the subsequent year. The participants were presented with lineups consisting of 20 plots, where a residual plot was embedded along with 19 null plots, drawn with data simulated using the residual rotation technique. The study considered two primary forms of residual departures in multiple linear regression, namely non-linearity and

heteroskedasticity. To enrich the visual features, different fitted value distributions, including normal, uniform, lognormal, and discrete, were also incorporated.

As shown in Figure 2 and Figure **??**, the study revealed that appropriate conventional residual-based statistical tests are more sensitive to weak residual departures from model assumptions compared to visual tests evaluated by humans, leading to excessive rejections even when downstream analysis and outcomes would not be significantly impacted by the small departures from a good fit. Specifically, conventional tests conclude that the model fit has issues nearly twice as frequently as humans would, and they frequently reject departures in the form of non-linearity and heteroskedasticity that are not visible to humans. For instance, based on the row of scatter plots at the bottom of Figure 2, we might argue that the non-linearity is not sufficiently problematic until an effect size of around 3 or 3.5. The RESET test would reject closer to an effect size of 2, but the visual test would reject closer 3.25.
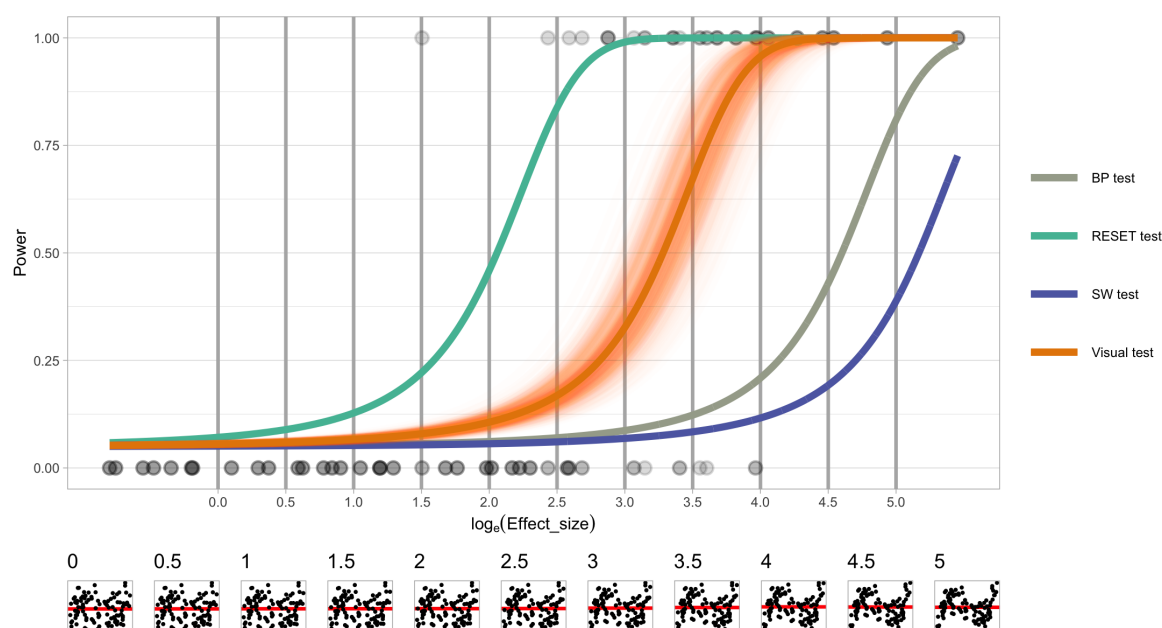

Figure 2: *Comparison of power between different tests for detecting non-linearity. The power curves are estimated using logistic regression, and the horizontal lines of dots represent non-reject and reject results from human observers for each lineup. The visual test has multiple power curves estimated from bootstrap samples. The row of scatterplots at the bottom are examples of residual plots corresponding to the specific effect sizes marked by vertical lines in the main plot.*

These findings emphasize the crucial role of graphical diagnostics and support the integration of visual inference into regression diagnostics. Moreover, they provide a compelling rationale for the development of an automated visual inference system to evaluate lineups of residual plots. The comprehensive details of the research methodology, along with other intriguing findings can be found in the attached paper.
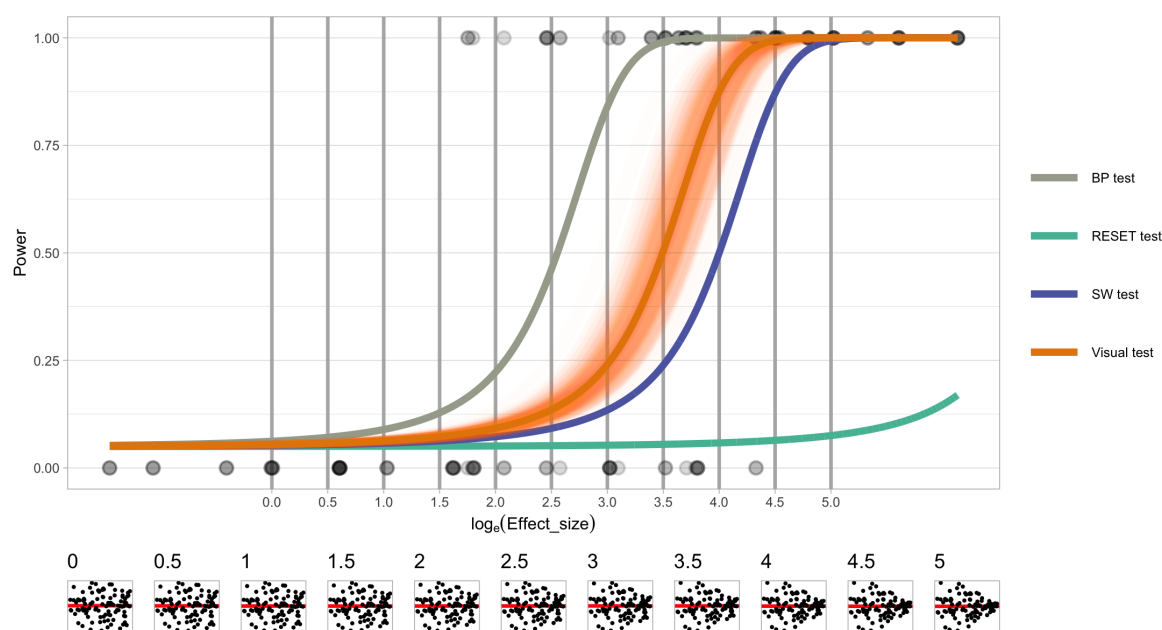
Figure 3: *Comparison of power between different tests for detecting heteroskedasticity. Main plot shows the power curves, with dots indicating non-reject and reject in visual testing of lineups. The multiple lines for the visual test arise from estimating the power on many bootstrap samples. The row of scatterplots at the bottom are examples of residual plots corresponding to the specific effect sizes marked by vertical lines in the main plot.*

We have also tried to develop a prototype of the automatic visual inference system with pure simulated data. The model

2 Thesis structure

The thesis is structured as follows. The first chapter describes the background on regression diagnostics, visual inference and computer vision models. The second chapter will be identical to the attached paper which focuses on the comparative study between visual testing and conventional testing in the application of regression diagnostics. The third chapter will describe the development of the a computer vision system to evaluate residual plot

The fourth chapter will detail the

The fifth chapter will be the discussion of the thesis and future work.

The first chapter of the thesis will be the introduction The second chapter of thesis will be the

The first project develops a prototype of automatic visual inference system for evaluating lineups of residual plots, with a focus on the classical normal linear regression model given it is one of the simplest predictive models. The automatic system is identical to the lineup protocol except evaluators

Table 1: *Timetable till thesis submission*

Date	Event
2023	
April	Submit the abstract of the first paper to Australian Statistical Conference (ASC)
May	Submit the first paper
June	Submit a poster for the first paper to Institute of Electrical and Electronics Engineers (IEEE) Visualization Conference
July	Leave for a month
Sep	Finalize the computer vision model
Oct	Attend the IEEE Visualization Conference
Nov	Start the web interface development
Dec	Attend the ASC
2024	
Mar	Submit the second paper
Aug	Submit thesis

are replaced by computer vision models. The computer vision models are trained by using data simulated from linear models with violations of different classical assumptions, such as linearity and homoscedasticity. Data of human performance on evaluating residual plots generated under the same simulation setting is collected by conducting online human subject experiments, such that the comparison between the power of human subject-assessed visual tests and the system-assessed visual tests can be made. Moreover, factors that affect the performance of the automatic system are studied for improving the architecture and design of the computer vision models.

The second project aims to extend the automatic system to lineup protocol with no assumptions on the type of the data plot and the data generating process. It only requires the protocol to asks the evaluators to select the most different plot(s) from the lineup. The automatic system will be built upon image similarity produced by computer vision models.

The third projects aims to package and deploy the automatic system as an adaptive online application such that empirical data can be collected and used in improving the system. Online machine learning technique will be used to update the weights of computer vision models dynamically.

3 Timetable

The timetable of my PhD study from April 2023 to August 2024 is provided in Table 1.

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