Identifying clinically relevant thresholds in automated assessment
A capstone project

Description The recent innovation of automated hand-held pupillometers changed how clinicians evaluate the pupillary light reflex (McNett et al., 2017; Olson et al., 2016). The new technology allows clinicians to capture pupil movements at precision to the hundredth of a second and provide new measurements unavailable from a manual exam. However, there are currently no sufficient statistical evidence to describe the new normal for neurologically impaired patients because this technology is recently implemented. In particular, researchers has find the constriction velocity (CV) to be high associated with acute brain injury index (e.g. Olson and Fishel, 2016; Shoyombo et al., 2018), where the CV reflects the change in pupil size from baseline to the smallest value over time. Currently, the threshold for CV is 0.8 mm/s meaning patients with a CV less than 0.8 mm/s were considered having a higher risk of experiencing an acute ischemic stroke and prevention treatments were given. This threshold is chosen based on historical evidence decades before the new pupillometers is available (Ellis, 1981). This proposal aims to recommend a statistical sound threshold using data from the Establishing Normative Data for Pupillometer Assessments in Neuroscience Intensive Care (END-PANIC) Registry (Olson et al., 2017).

Approach In this capstone project, we will develop a machine learning approach to provide a statistical meaning thresholds for clinically relevant changes in automated assessment. The main idea is to choose a threshold that gives favorable predictive results. Let $X(t) = \{X_1(t), \ldots, X_d(t)\}^\top$ be a d-dimensional vector of possible time dependent covaraites. Without loss of generality, let $X_1(t) = \text{CV}(t)$ be the CV measurement at time t. Let τ be a fixed cutoff point, consider the logistic model where $I\{\text{CV}(t) < \tau\}$ is included in the model instead of the continuous value $\text{CV}(t)$,

$$g(E\{Y|X\}) = \alpha + \boldsymbol{X}(t)^\top \boldsymbol{\beta} = \alpha + \beta_1 I\{\text{CV}(t) < \tau\} + \ldots + \beta_d X_d(t),$$

where α is the intercept, $\boldsymbol{\beta}$ is a vector of regression coefficient, g is the logistic link function, and Y is a binary variable that indicates the existence of a stroke through out the hospital stay. Baseline covaraites such as age, gender, and race will be included as $X_i(t) \equiv X_i(0)$, for $i > 1$. We propose to choose a cutoff point τ that maximizes the area under the curve (AUC) of a receiver operating characteristic curve (ROC). Following the derivations in Pepe et al. (2003), maximizing AUC is equivalent to maximizing the concordance measure. The proposed algorithm to detect an optimal cutoff point is outlined below:

Step 1. Split the data into training and testing datasets by subject id's.

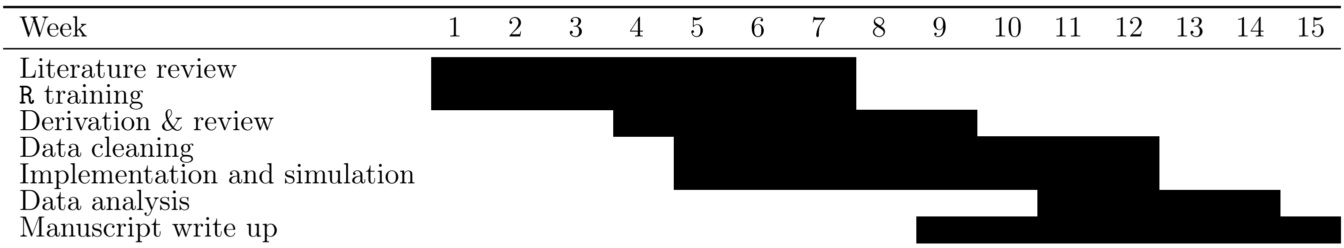
Step 2. Initialize $m = 1$, fit the logistic regression model under the training set, given a cutoff point τ_m.

Step 3. Calculate the CON using the testing set and store it as A_m.

Step 4. Repeat Steps 2 and 3 for $m = 2, \ldots, M$, where M is the total number of cutoff points to be tested.

Given the size of END-PANIC data, the proportions of the training and the testing datasets in Step 1 will provide a good balance between modeling building and validating.

Expected deliverables A final report is expected. In addition, we propose the following time line for the project:



Necessary skills expected in students Students should be familiar with regression models and model building. Students are also expected to have good writing skills and programming skills.

References

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