# Mouse-Tracking a window intro decision making.

We have argued for mouse-tracking as an excellent tool for obtaining a rich, contextual and continuous measure for cognitive processes, avoiding averaging techniques used in the otherwise similar paradigm of eye-tracking (Spivey et al., 2005). Mouse-tracking analysis procedures are currently very ambiguous, lacking a supported clear analysis pipeline. Such ambiguity has emerged several diverging paths of mouse-tracking analysis, thereby weaking the entire field and making comparative analysis difficult (Schoemann et al., 2021). An attempt to standardize mouse-tracking analysis while still keeping the core flexibility that mouse-tracking contains was conducted by Maldonado et al., (2019). Maldonado’s et.al., (2019) contribution to the field of mouse-tracking analysis consist mainly of linear-discriminant-analysis (LDA) classifier trained on a forced-switch task simulating the expected mouse trajectory following a decision task with a two-step processing. By replicating Dale & Duran's, (2011) study on linguistic negation as two-step process they obtained data for testing their LDA classifier using [Area Under the Receiver Operating Characteristic curve](https://en.wikipedia.org/wiki/Receiver_operating_characteristic#Area_under_the_curve) [[1]](#footnote-1)(AUROC) as a metric for performance. We will be investigating the possibilities for applying their framework to a broader scope of the mouse-tracking literature by replicating a known experiment on dynamical processing using mouse-tracking ie. (Spivey et al., 2005) work on decision processing in phonological similarity. Followed up by a discussing advantage and disadvantages of LDA AUROC and First we will walk through the experimental setup and ideas behind (Maldonado et al., 2019), followed up by an introduction to our experimental idea and design.

## Calibration Data:

The first step of Maldonado et al., (2019) were to create a baseline for the LDA classifier to train on. An “ideal” mouse-trajectory a two-step processing decision task were simulated using a forced dual-choice switch task. The experiment is initiated with two possible answer boxes (blue) & (red) and a frame at the edge of the window with the same possible colors. The job of the participants is to repeatedly select the box with the matching color of the frame at the edge across the 88 trials. To induce an element that would simulate a two-step processing task twenty-four of the eighty-eight trials had a “switch” condition with the remaining being “straightforward” with no manipulation. “Switch” trials involved the frame changing color to the opposite, forcing participants to change mouse-trajectory, and thereby simulating a switch decision making. Point of change were dependent on the y-coordinate which varied between 40%, 70% and 90% of the way to the target on the y-axis allowing for the LDA classifier to have data with varying temporal aspects of the switched decision (Maldonado et al., 2019).

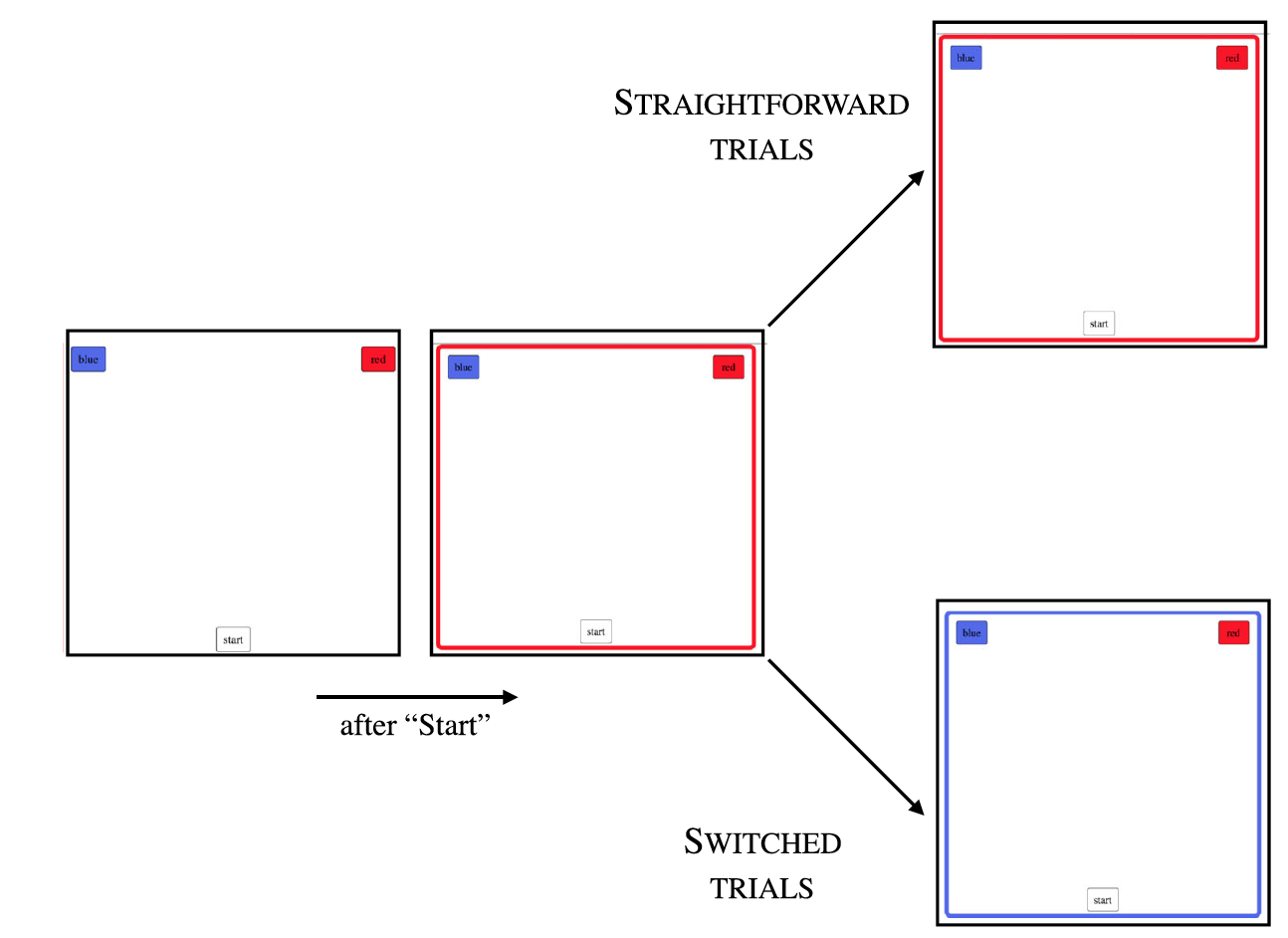


Figure 1 (Maldonado et al., 2019), Experimental design of the Calibration experiment.

### Training of LDA on calibration data.

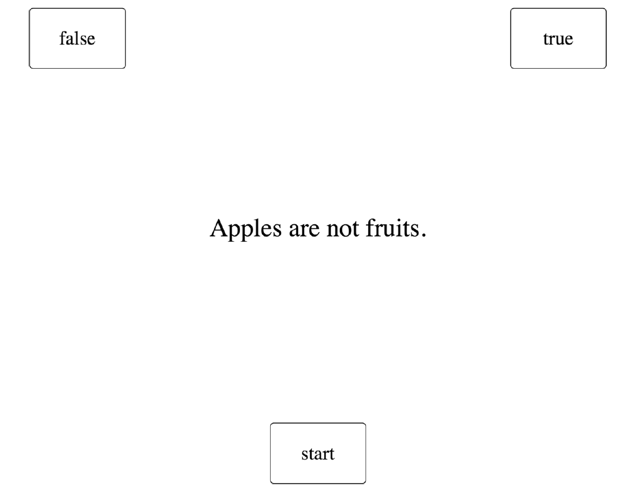
A pipeline for training the LDA classifier is as follows, **1)** Normalize and flip (X, Y) coordinates by setting start point = (0,0), end point = (1,1). Based on the spatio-temporal information calculate the non-linear Euclidean velocity and acceleration. Finally, time-normalize the data into 101 steps. **2)** Even though Maldonado et al., (2019) didn’t report it in their paper we ran through their analysis script and found them to standardize all features based on the Z-distribution with a mean = 0 and SD = 1 prior to the conducting of the principal component analysis (PCA) (*Importance of Feature Scaling*, u.å.). This is important since is gives equal weight to all features when calculating the covariance matrix used for PCA. The PCA removed any collinearity which otherwise would be an issue for any regression or classification model, leaving us with 13 PCA features to feed to the LDA classifier. 3) The 13 PCA features fed to the LDA classifier were based on a varying X matrix containing one of the combinations showed in table 1. An in-depth review of LDA and PCA will be take place later in the article. By comparing their classifiers with different PCA features extracted from the varying combination of predictors shown in table 1 were Maldonado et al., (2019) able to gather information on which mouse-features were the most important for classifying decision processes. A 10-fold cross-validation(cv) on all their models concluded that the most important feature for classifying “straight” vs. “switched” trial were the coordinates.

Table 1 (Maldonado et al., 2019)

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## Extending the LDA classifier to negation data:

For testing whether the classifier is a useful tool for analyzing mouse-tracking data it must generalize beyond the “simulated” decision data in the forced switch task. To test the generalizability of their classifier Maldonado et al., (2019) had to test it on more ecological mouse-tracking data. They choose to replicate Dale & Duran, (2011) study on sentence negation with an hypothesize that if sentence negation followed the same two-step processing as in the forced calibration task the LDA performer would perform similarly. Participants were with a screen like figure 2. A true or false sentence would be presented in the middle of the screen either including or excluding a negation, i.e., “elephants are not small” or “elephants are not large” (Dale & Duran, 2011). The job of the participants was to evaluate the statement and select the corresponding false or true statement. Maldonado et al., (2019) managed to replicate the original studies finding of a significant increase in x-flips when the statement was truth and included a negation.

Having verified the replication of the original Dale & Duran, (2011) findings the LDA classifier could now be tested to evaluate its generalizability and advantages.

Figure 2, Dale & Duran, (2011) Negation study.

1. For information on AUROC https://towardsdatascience. com/understanding-auc-roc-curve-68b2303cc9c5. [↑](#footnote-ref-1)