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What can Associative Learning do for Driving?

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Abstract

To improve road safety, it is important to understand the impact that the contingencies around traffic lights have upon drivers' behavior. There are formal rules that govern behavior at UK traffic lights (see The Highway Code, 2015), but what does experience of the contingencies do to us? While a green light always cues a go response and a singleton red a stop, the behavior linked to amber is ambiguous; in the presence of red it cues readiness to start, while on its own it cues "preparation" to stop. Could it be that the contingencies between stimuli and responses lead to implicit learning of responses that differ from those suggested by the rules of the road? This study used an incidental go/no-go task in which colored shapes were stochastically predictive of whether a response was required. The stimuli encoded the contingencies between traffic lights and their appropriate responses, for example, stimulus G was a go cue, mimicking the response to a green light. Evidence was found to indicate that G was a go cue, while A (which had the same contingencies as an amber light) was a weak go cue, and that R (a stop cue) was surprisingly responded to as a neutral cue.

Keywords: Associative learning; response inhibition; driving behavior

Introduction

Driver error is a critical factor in 94% of road incidents (U.S. Department of Transportation, 2015). Specifically, with 22% of urban road collisions caused by drivers ignoring stop signals at traffic lights (Retting, Williams, Preusser, & Weinstein, 1995) there is a need to address dangerous behavior at traffic lights. A possible solution is the use of cameras to enable people to be penalized when they cross a red traffic light. This can lead to safer driving and increase compliance (Baratian-Ghorghi, Zhou, & Franco-Watkins, 2017) but it may be that such a reactive approach does not address the root cause of the behavior. Our question is: What role do the contingencies of traffic lights have upon drivers' behavior?

The UK traffic light signal follows a set pattern, changing from green to amber to indicate drivers should prepare to stop; then to red meaning stop; then to red and amber to tell drivers to get ready to start, and finally back to green (see Figure 1). Past research on the contingencies between traffic lights and behavior has included altering the timings of the light pattern (Jason, Neal, & Marinakis, 1985) or investigating how personal factors are predictive of behavior around traffic lights (Palat & Delhomme, 2016). This work has been in the context of engineering solutions to increase road safety, rather than looking at how the contingencies of the lights *per se* may cue a certain behavior.

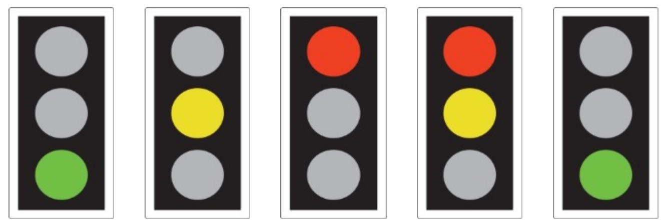

Figure 1: The UK traffic light sequence, starting from left.

The Current Studies

These studies investigated the effect that the contingencies between traffic lights and permitted responses (stopping/starting) have upon driving behavior. We focused on the contingencies around amber traffic lights. While a green light always cues a go response and a singleton red a stop, the behavior linked to amber is ambiguous; in the presence of red it cues readiness to start, while on its own it cues "preparation" to stop. By using an incidental go/no-go task (Bowditch, Verbruggen, & McLaren, 2016), these experiments exposed subjects to the contingencies between traffic light signals and stopping and starting, and so enabled us to see what effect this had on behavior.

Study 1

What would one expect based on standard associative theories (Rescorla & Wagner, 1972)? If we begin by ignoring the sequential information inherent in our typical experience of UK traffic lights, and imagine that people treat a solo amber traffic light as a warning that they may have to 'stop' and a red and amber compound as 'go' this leads to the following set of contingencies, where '+' denotes 'stop' and '-' denotes 'go', and R, A, and G stand for cues playing the role of red, amber and green respectively: R+, G-, A?, RA-. We used '+' to denote a stop response as the procedure was designed to cause stopping to be the effective outcome learned. It is felt that this design, rather than the traditional '-' to denote 'stop', is more realistic. The default when driving is to make progress and so the outcome at traffic lights will be whether one must stop or not, with stopping requiring an action, i.e., depression of the brake pedal.

The “?” encodes the ambiguous nature of amber lights. A solo amber is not always seen as a ‘stop’ cue with nearly four out of ten drivers saying they rarely stop at amber lights (Thrifty, 2011). Accordingly, in implementing this contingency, A will be treated as 50% stop rather than always '+', i.e. A±, rather than A+. Clearly R will become associated with stopping to some extent, and G with not stopping (i.e. going), The RA- contingency will tend to cause A± to become a go cue, while the A± cue might promote a weak stop association to amber. The net effect may be that A will become a go cue, i.e. more like G than R, and will significantly differ to a control just trained ± (average of I and P, see Table 1).

Method

Design and Subjects The experiment used a within-subjects design comparing performance on experimental versus control cues. Subjects had to be 18-65 years old, have normal or corrected vision and not be color blind. The statistical techniques used to analyze the results meant that traditional power analyzes were inappropriate, with the study using a sample of 50 in line with past research (Bowditch et al., 2016). **S**ubjects from the University of Exeter participated in exchange for payment of £5 or one course credit. Six subjects were replaced for having commission (1) or omission errors (5) greater than two interquartile ranges from the upper and lower quartile. Of the final sample, 41 were female with an overall mean age (with one missing data point) of 21 (SD = 5.43).

To reduce the likelihood of subjects explicitly learning the experimental design, cues G and RA were set at 75% go and R set at 75% stop – this also enabled the development of learning to be investigated though commission and omission errors. Cue A and the control cues B, I, P, IP, and J were set at 50% stop. The first four control cues matched the experimental cues, e.g. B was a control for G, I controlled for R, P controlled for A, while IP controlled for RA. Cue J was used for tracking purposes (see later).

Incidental go/no-go task The task required subjects to press a key or withhold a response depending on the color of a presented circle stimulus. Each trial started with two colored shape cues being presented for 250ms on a 50% grey background. Subjects were informed that these cues indicated that the trial was beginning but, in fact, they also stochastically predicted whether a subject was required to respond. There was one calibration, eight training, and two test blocks with 10 second breaks between blocks.

Throughout the task a white horizontal bar measuring 19mm by 4mm was displayed in the center of the screen. Colored shape cues measuring 19mm^2 were presented in vertical alignment above and below and equidistant from this bar. On single cue trials (e.g. G-) the cue appeared in both the top and bottom positions, while on compound trials (e.g. RA-) each cue was randomized to appear at either position. Following presentation of the cues on go trials, a 19mm diameter white circle appeared to the left or right of the central bar (separated by 22m edge-to-edge). This indicated to subjects that they needed to make a spatially congruent response, e.g. a left side response (‘x’ on a standard QWERTY keyboard) when a left-side circle was displayed (right-hand circles required a ‘.>’ key press). On no-go cues a colored circle was displayed informing subjects that they needed to withhold a response (see Figure 2 for schematic of a trial). This circle was one of four colors chosen at random (see below) and differed from the colors used for the cues. For both trial types, the circle appeared equally to the left or right of the cue, and the color of the no-go signal was distributed equally across trials. Subjects received on screen feedback. For commission errors, regardless of congruency of response or incorrect keypress feedback read ‘No response required!’ For omission errors feedback was ‘You should have responded’. On go trials subjects received feedback on incorrect key presses (‘Incorrect key pressed, use X or .>’) and wrong direction key presses (‘'Press the key that matches the side the white circle appears on'). All feedback was displayed for 500ms and was accompanied with a 400Hz tone for 150ms delivered through closed headphones. A tracking procedure for the whole task was applied to both go and no-go trials based on cue J and was a 3-down/1-up procedure, so that for every three correct trials the maximum response window shortened by 50ms, whilst an error resulted in the window increasing by 50ms. The window started at 750ms with the calibration phase setting the initial window for each subject. There was a variable interval of 250 to 500ms between trials.

The same cues were used throughout the experiment but were randomized for each subject. The color of the cues and no-go circles were randomized for each subject and sampled from the HSB color-space (Joblove & Greenberg, 1978) by selecting equally spaced hues whilst constraining saturation (75-100%) and brightness (50-100%).

Table 1: Summary of Study 1 design. Letters represent colored shapes. Trials are go 75% of the time (-), stop 75% of the time (+), or stop 50% of the time (±). At test all trials are 50% stop and the cues are non-predictive.

Phase	Blocks	Trials p/block	N p/type	Design		
Calibration	1	48	48			J±
Training	8	144	16	G-, R$_+$, A±, RA-	B±, I±, P±, IP±	J±
Test	2	144	16	G, R, A, RA	B, I, P, IP	J

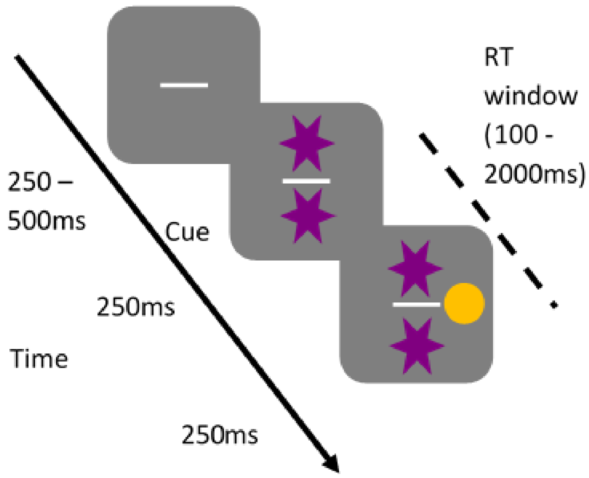

Figure 2: Schematic of a single cue stop trial.

Results

Data was processed and analyzed using R (R Core Team, 2016). Due to the need for subjects to respond at least once per cue to obtain RT measurements data was averaged by cue by block with RTs of error trials being excluded. Training data was then collapsed into halves to reduce data loss. We developed linear mixed-effects models using lme4 (Bates, Mächler, Bolker, & Walker, 2015). Models for the training phase estimated fixed effects of cue and training half whereas models for the test phase estimated fixed effects for cue and test block. Subject was entered as a random intercept and a random slope term was included for the effect of cue. We used an information-theoretic approach based on the Akaike Information Criterion (Akaike, 1974) to compare models. The model with the lowest score was considered to be the best fit for the data, and this is the reported model for each DV. Homoscedasticity and normality of the residuals were confirmed using a graphical approach and by reference to the central limit theorem. For the inferential statistics continuous predictors were standardized (mean of 0, standard deviation of 1) to allow for contrast of effect sizes between models (Schielzeth, 2010) and mean RTs were centered to aid interpretation of the results (Dalal & Zickar, 2012). Conditional R^2 values were estimated using the MuMIn package (Barton, 2017). The significance of fixed effects was assessed using Wald *F* tests with Satterthwaite-approximated degrees of freedom through lmerTest (Kuznetsova, Brockhoff, & Christensen, 2016). Parameter estimates are presented with ±SE and effect sizes were calculated from Judd, Westfall, and Kenny (2017). All tests are two-tailed unless stated. Omission data is not reported due to the scarcity of data. Contrasts focused on A± vs. R+, G- vs. B±, R+ vs. RA-, and, crucially for the hypothesis, A± vs. average of I± and P± (see Figure 3 for graph of the raw means). To control for multiple comparisons the alpha level was corrected to .013.

Reaction times Training RT data was analyzed with a random intercept ($\sigma^2 = 0.90$) model with the main effects of the fixed effects (conditional $R^2 = 0.89$). The main effect of cue was significant $F(8,841) = 2.03$, $p = .040$ yet all contrasts were not. At test, a random intercept ($\sigma^2 = 0.68$) model with the main effects of the fixed effects (conditional $R^2 = 0.68$) was used. There were no significant main effects. The predicted faster RT for G relative to its control B was found, $b = 0.18 \pm 0.08$, $t(841) = 2.26$, $p = .012$ (1-tail), $d = 0.18$, with subjects having faster RTs for G (M = 367. 29ms, SD = 64.71) than for B (M = 380.18ms, SD = 64.75).

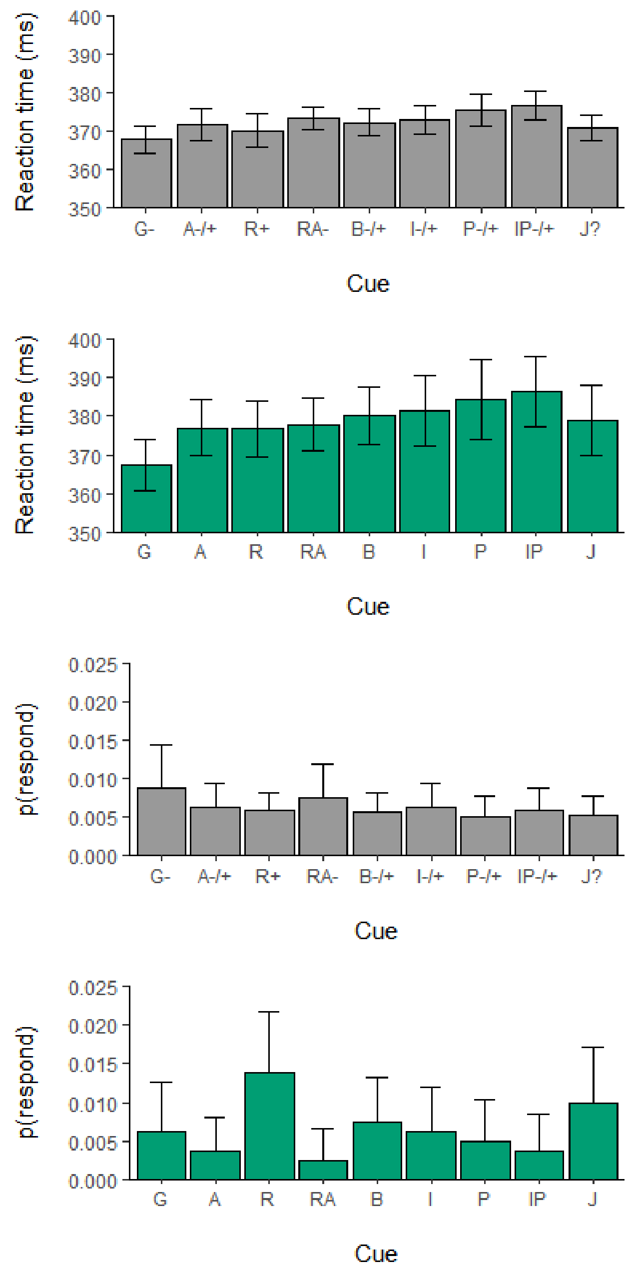

Figure 3: Mean RT and p(respond) by training (grey) and test (green) phases for Study 1. Error bars are within-subject confidence intervals (Morey, 2008).

Commission errors Data was analyzed across training with a random intercept (σ^2 = 0.06) and slope model with the main effects of the fixed effects (conditional R^2 = 0.21). There were no significant results. At test, random slopes models did not converge. The best-fit model was a random intercept (σ^2 = 0.03) model with the main effects of the fixed effects (conditional R^2 = 0.05). There were no significant fixed effects. There was a significant difference between R vs. RA, b = -0.38 ±0.14, t(841) = -2.79, p = .005, d = 0.39, with subjects displaying more errors for R (M = 0.014, SD = 0.043) than for RA (M = 0.003, SD = 0.018), and for A vs. R, b = 0.34 ± 0.14, t(841) = 2.48, p = .013, d = 0.35, with subjects displaying more errors for R (M = 0.014, SD = 0.043) than for A (M = 0.004, SD = 0.021).

Discussion

The results from the training phase suggest that subjects did not learn the discrimination. However, at test G had clearly become a go cue on the RT measure. In contrast to our hypothesis, the evidence for cue A being a go cue at test is not strong, but it does not seem to be a particularly strong stop cue either. The unexpected findings at test for p(respond), with subjects displaying significantly more commission errors for R (notionally a stop cue) than for RA (a go cue), contradict the RT data and suggest that R is more neutral than stop.

There are, however, two issues with the experimental design that need addressing. First, in attempting to mimic the contingencies of UK traffic lights the overall experimental design was unbalanced; subjects were more likely to ‘go’ than to ‘stop’. While there were two go cues, there was only one stop cue with the rest being 50/50. Second, the assumption that the effective outcome being learned is to stop needs evaluating. The feature-positive effect can be used to do this. We know that humans (Newman, Wolff, & Hearst, 1980) show greater excitatory than inhibitory learning. Consequently, if the outcome of a task is stop (+), then the discrimination between cues A- vs. AB+ (a feature-positive discrimination) will be acquired more readily than the feature-negative discrimination P+ vs. PQ-. The feature-positive discrimination requires the excitatory learning to B as well as the extinction of A, whereas the feature-negative discrimination requires a subject to first learn that P is an excitatory cue before learning that Q is an inhibitor, which takes longer. Knowing that the feature positive discrimination will be learned best one can see what the outcome of a task is. Noting that in the current task ‘+’ represents ‘stop’ the pair R+, RA- is a feature-negative pair, a feature-positive discrimination needs to be added to the design. If stop is the outcome then this new pair should be learnt more readily than R+, RA-.

Study 2

Two changes were made to the design (see Table 2), 1) B± became B+ to reduce the tendency to go, and 2) I±, IP± became I-, IP+, and thus a feature-positive discrimination.

Method

Design and Subjects The design and inclusion and exclusion criteria were identical to Study 1. The hypothesis for A was changed and was now expected to differ significantly from its new control, P±. A power analysis using SIMR (Green & MacLeod, 2016) indicated that a sample size of 55 would give an 80.20% power to detect an effect for the test phase RT G vs. B contrast. Fifty-five subjects from the University of Exeter participated in exchange for payment of £5 or one course credit. Six subjects were replaced, one subject did not complete the experiment while five subjects meet the exclusion criteria. Of the final sample, 41 were female with an overall mean age of 19 (SD = 3.47). The task was identical to that of Study 1 bar the design changes outlined above.

Results

Results were processed and analyzed using the approach outlined in Study 1 with the addition of paired samples t-tests on the raw means comparing the differences between I- vs. IP+ and R+ vs. RA-. Cohen’s d for the t-tests were calculated using Lakens’ (2013) formula. Contrasts focused on I- vs. IP+, R+ vs. RA-, G- vs. B+, A± vs. R+, and, crucially for the hypothesis, A± vs. P± (see Figure 4 for graph of the raw means). To control for multiple comparisons the alpha level was corrected to .008.

Reaction time Training data was analyzed with a random intercept (σ^2 = 0.79) model with the main effects of the fixed effects (conditional R^2 = 0.79). There was a significant effect of training half, F(1, 926) = 39.71, p = < .0001, d = 0.18, with RTs being significantly faster in training half one (M = 383.66ms, SD = 39.72) than in training half two (M = 391.92ms, SD = 49.45) and a significant difference for cue, F(8, 926) = 6.64, p = < .0001. There was a significant difference in the feature-positive contrast, b = 0.24 ± 0.06, t(926) = 3.88, p = .0001, d = 0.24, with subjects having faster RTs for I- (M = 383.47ms, SD = 43.48) than for IP+

Table 2: Summary of Study 2 design. Letters represent colored shapes. Trials are go 75% of the time (-), stop 75% of the time (+), or stop 50% of the time (±). At test all trials are 50% stop and the cues are non-predictive.

Phase	Blocks	Trials p/block	N p/type	Design		
Calibration	1	48	48			J±
Training	8	144	16	G-, R+, A±, RA-	B+, I-, P±, IP+	J±
Test	2	144	16	G, R, A, RA	B, I, P, IP	J

(M = 394.27ms, SD = 52.09). The feature-negative contrast was non-significant, but a paired samples t-test data found a significant difference between the differences, $t(54) = -3.23$, $p = .002$, 95% CI [-19.35, -4.54], $d_z = 0.44$, suggesting that the feature-positive discrimination was easier to acquire than the feature-negative discrimination. The G- vs. B+ contrast was significant, $b = 0.32 \pm 0.06$, $t(926) = 5.17$, $p = < .0001$, $d = 0.32$, with subjects having faster RT for G- (M = 378.19ms, SD = 40.24) than for B+ (M = 392.57ms, SD = 44.70). At test, a random intercept ($\sigma^2 = 0.64$) model with the main effects of the fixed effects (conditional $R^2 = 0.64$) was used. Only the effect of cue was significant, $F(8, 926) = 3.07$, $p = .002$. Both the feature-negative and feature-positive contrasts were non-significant as was the difference between the differences (though the feature-positive contrast was significant at the standard alpha level, $p = .021$). There was again a significant difference for the G vs. B contrast, $b = 0.25 \pm 0.08$, $t(926) = 3.13$, $p = .002$, $d = 0.25$, with subjects having faster RTs for G (M = 392.08ms, SD = 70.05) then for B (M = 408.89ms, SD = 65.19).

Commission errors Training data for p(respond) was analyzed with a random intercept ($\sigma^2 = 0.04$) and slope model with the interaction term and main effects of the fixed effects (conditional $R^2 = 0.37$). In the model only the main effect of training half was significant, $F(1, 756) = 7.51$, $p = .006$, $d = 0.16$. It should be noted that the interaction term was only kept in the model as random intercept models failed to converge otherwise and thus interaction terms for contrasts will not be reported. The I- vs. IP+ contrast was not significant, however the R+ vs. RA- was, $b = 0.51 \pm 0.18$, $t(122) = 2.78$, $p = .006$, $d = 0.65$, with subjects making more commission errors for RA- (M = 0.008, SD = 0.024) than for R+ (M = 0.003, SD = 0.009). The difference between the differences for these two contrasts was not significant. The G- vs. B+ was significant at the standard alpha level ($p = .025$, one-tail). Test phase data was analyzed with a random intercept ($\sigma^2 = 0.01$) model with the main effects of the fixed effects (conditional $R^2 = 0.03$). In the model there were no significant main effects or contrasts, but the trend for more commission errors for R than for RA was present, though not significant.

Discussion

Study 2 found evidence for the feature-positive effect (with + being the outcome). In both phases for RT the feature-positive discrimination was learnt better than the feature-negative, with the difference between the two being non-significant for commission errors. This suggests that the outcome of the task is indeed stopping, with subjects looking to successfully withhold rather than respond. As with Study 1 subjects learnt that G was a go cue. Counter to the hypothesis there was no significant difference between cues A and P at test. Unlike Study 1 the contrast for R vs. RA commission errors at test was non-significant, however there is once more a trend for more commission errors for R rather than RA, whereas, in theory one would expect fewer commission errors for R.

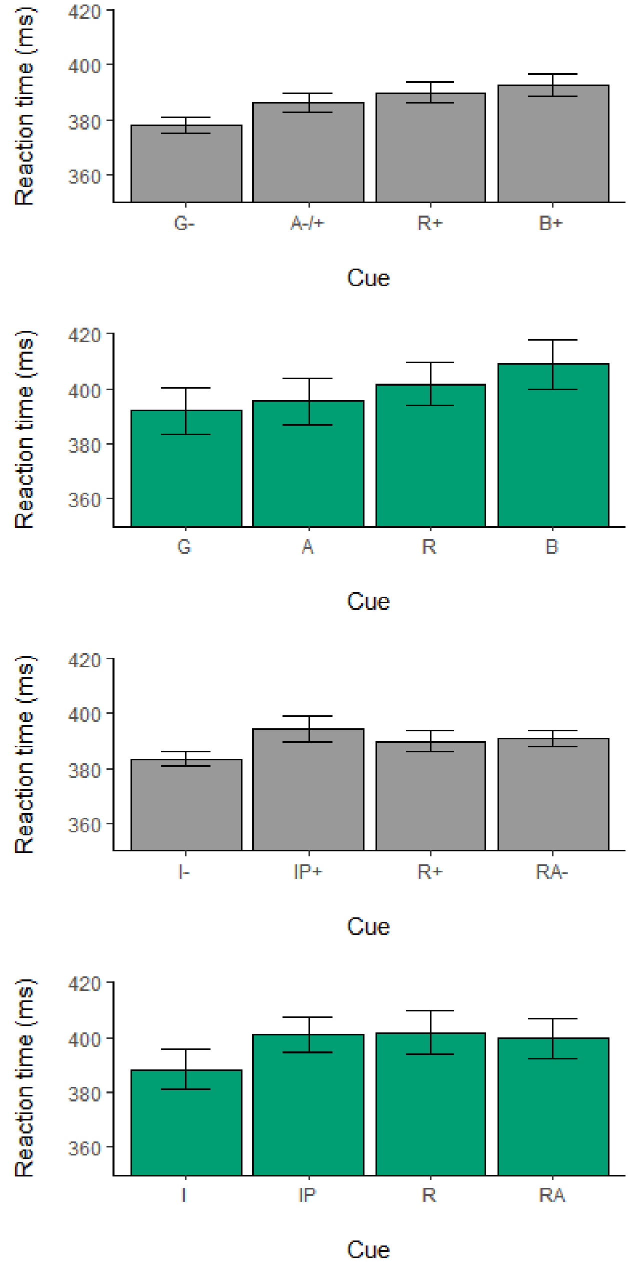

Figure 4: Mean RT by training (grey) and test (green) phase for Study 2. Top two panels: traffic light cues and cue B as an anchoring stop cue. Bottom two panels: feature positive and feature negative contrasts. Error bars are within-subject confidence intervals (Morey, 2008).

General Discussion

Across both studies we found evidence that subjects learnt that cue G was a go cue, giving us confidence that subjects were experiencing the incidental go/no-go task as expected. In terms of the main question regarding the effect of experiences at amber traffic lights on behavior, in Study 1 cue A was similar to a notional stop cue (R), yet in Study 2 cue A seems to be have shifted towards cue G, a go cue. Overall, this leaves the impression that amber is a weak go cue rather than the stop cue that traffic laws would suggest. Though the results from Study 1 suggested that a stop cue (R) was unexpectedly experienced as something of a go cue, the effect was not significantly present in Study 2, leaving us with a sense of red as a somewhat neutral cue. Considering that the task has been shown to promote stopping this result is rather surprising. One might think that when the default is to go, and one is looking out for a stop signal this is when learning about red will be optimal, but our evidence suggests that this is not the case. This is certainly an avenue worth further exploration as it indicates that the contingences of UK traffic lights prevent effective learning of stop cues, at least in a stop task set.

These studies demonstrate how basic science can inform applied research, highlighting the merit of addressing behavior at amber traffic lights. With amber being a go cue interventions should focus on techniques that could change the automatic response to amber to one of stop. In summary, the results from the two studies demonstrate how the contingencies of UK traffic lights affect driver's behavior, leading to both amber and red lights being experienced in a manner likely to increase risky driving and contrary to the rules of the road.

Acknowledgments

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