Humans Out-Learning the Machine: Support Vector Machines Applied to fMRI of Human Motor Learning

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INTRODUCTION Most fMRI analysis techniques make the implicit assumption that the data (arising from an MR system's measurement of a subject's brain response) is constant over repetitions of a stimulus. For behavioral tasks showing limited evidence of human learning or adaptation, the assumption of consistency is warranted within reasonable limits. In general, though, a human subject is prone to factors such as habituation, learning, and fatigue. This study aims to explicitly examine performance of learning algorithms on a time-varying system. Specifically, we are interested in how behaviorally demonstrated learning by a subject corresponds with changes in the image data and if this is directly observable through statistical machine learning techniques. We use a complex finger sequence that provides directly observable human learning (increased pace and accuracy over time). We compare this direct evidence of learning with changes in performance of multivariate support vector machine regression (SVR) models [1].

METHODS Paradigm: The motor task was adapted from [2]. Five healthy, right-handed volunteers were asked to perform a complex button press sequence (middle, pinkie, ring, index) with their left hand as accurately and rapidly as possible on a four-button, fiber optic button box (Current Designs, www.curdes.com). An experimental run consisted of four 16 sec periods of continued button presses interspersed between five 16 sec control periods. Periods were visually guided, with control periods displaying a fixation cross and motor periods displaying text reminding the volunteer of the proper finger sequence. The scanning session consisted of 4 repeated fMRI runs, each spaced approximately 5 minutes apart. Volunteers were instructed not to mentally rehearse when not overtly performing the task. Imaging: fMRI data were collected on a 3T Siemens Trio, with 27 axial EPI slices (TR/TE = 2000/31 msec, voxel=3.4 × 3.4 × 5 mm). The stimulus display software used was Presentation® (Ver. 0.76, www.neurobs.com). Analysis: The fMRI runs were slice time corrected, registered to the first scan of the first run, and screened for motion in AFNI [3]. Scans during motor blocks from run 1 were used to build a multivariate SVR model relating all brain voxels to the number of button presses at each TR within these blocks. For each subject, models from run 1 were used to estimate the button rate in successive runs. In addition, GLM-based regression of button presses was performed at each voxel in a concatenated data set of the 4 run session.

RESULTS All subjects were able to maintain accuracy while increasing number of button presses per trial. The GLM results agree well with motor learning findings in [4]. Specifically, we observed left rostral anterior cingulate, orbitofrontal cortex and left posterior cingulate. In addition large portions of the cerebellum correlated with the increased button presses across the 4 runs. As indicated in Table 1, SVR errors had a strong tendency to increase with time. Examination of residuals (not shown) demonstrated that these models were biased to the button frequency of the training data, tending to underestimate future data. As also indicated by Table 1, these errors had a strong positive correlation with the median number of button presses per run. An example of this for subject 5 is illustrated in Fig. 1.

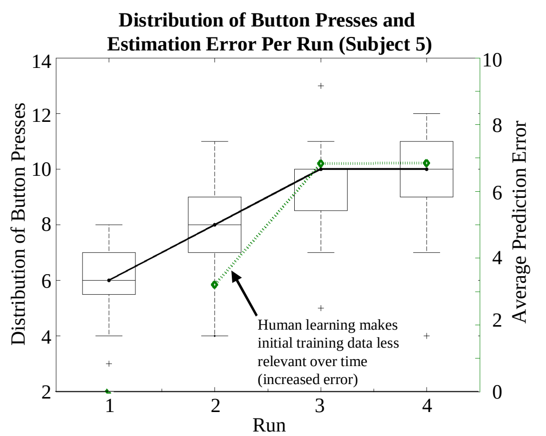

Figure 1. Box plots and connecting black line show distribution and median of button rate. Green line (right axis) shows ave. estimation error for SVR model trained on run 1.

Subject	Estimation Error Button Presses Run 1	Run 2	Run 3	Run 4	Button Press Correlation r
1	-- 4	0.51 4	0.57 5	1.40 6	0.897
2	-- 4	1.18 5	1.42 5	4.48 5	--
3	-- 4	0.96 5	1.16 6	2.04 7	0.941
4	-- 3.5	1.21 4.5	1.17 5	1.91 5	0.457
5	-- 6	3.20 8	6.83 10	6.85 10	1

Table 1. Estimation error of SVR model trained on run 1and correlation with median number of button presses.

DISCUSSION AND CONCLUSION We have demonstrated that human learning is directly observable through increased prediction error in multivariate SVM regression models of fMRI data. As a practical matter, these temporal changes are often a hindrance to the analysis process, but for effects such as learning or fatigue they represent a fascinating dynamic component to neuroimaging experiments. We have chosen motor learning as a prime example of this phenomenon as it is supported by existing neuroimaging literature, and lends itself to behavioral recordings that can be used as an external measure of learning. We have shown that such tasks can be used as model systems to study data non-stationarity. Future studies will focus on relating temporal changes in activation patterns to learning algorithms as well as development of approaches to compensate for losses in prediction accuracy arising from subject learning or adaptation. **REFERENCE** [1] Vapnik, V. The Nature of Statistical Learning Theory, 1995. [2] Rao, S.M., et. al. 1993. Neurology **43**, 2311-2318. [3] Cox, R. W. 1996. Comp. and Biomed. Res **29**, 162-173. [4] Lafleur, M.F., et. Al. 2002. NeuroImage **16**, 142-157.
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