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**Behavioral and cortical evidence of implicit statistical learning of temporal visual
regularities**

PhD Thesis

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List of publications related to the thesis

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"Online measurement of learning temporal statistical structure in categorization tasks"

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"Visual linguistic statistical learning is traceable through neural entrainment."

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Introduction

Our nervous system collects a plethora of information from the environment surrounding us. The processing of this information amount directly would overload the system and the formation of meaningful perception would be impossible. The sensory system employs several methods to reduce the load on itself, e.g. sensory filtering, or segmentation based on the statistical properties of interstimulus relationship. This can reduce the sensory load by not processing redundant information again and again and it can also facilitate the sensory process since stimuli can become predictable and the cortical areas can anticipate the appearance of a stimulus. The consolidation of these above-mentioned neural mechanisms, the discovery, acquisition, and usage of environmental statistical information is called statistical learning (SL). Statistical learning (SL) has been a widely examined phenomenon for decades and there is a general agreement that it is a fundamental part of sensory processing and perception which can be observed across several modalities and paradigms.

Behavioral and neural evidence implies that results in different SL modalities are not interchangeable. Separate investigation of these phenomena is necessary to fully explore this cognitive function. Not only the modality, but the supervision of the paradigm affects the learning outcome. SL can emerge in unsupervised paradigms that is without any explicit instructions about the statistical information. Many studies implement a quasi-supervised manner, where participants are told about a hidden regularity, but the exact parameters remain untold. This leads to the participants actively searching for statistical relationships which can result in explicit knowledge and require different neural resources. Taking these reports into consideration we can conclude that not all SL findings can be grouped together without restraints and in many cases, we must treat these results as individual entities based on their modalities, supervision, and other parameters of the paradigm.

EEG is a suitable tool for the examination of SL considering its high temporal resolution which is able to detect short lived cortical changes regarding learning effects. Many oscillatory bands have been associated with statistical learning. The low frequency theta band (4-7 Hz) was found to be modulated by expectancy and learning which is not surprising since it has close ties to the working memory. Alpha oscillations (8-12 Hz) also showed a role in expectancy processing. Alpha power showed a negative relationship with transitional probability, since unexpected stimuli elicited greater alpha powers. Beta band (~20Hz) differences also appeared in both visual and auditory paradigms.

The two most studied SL modalities are the auditory and visual. As mentioned before, the results of different modalities and SL paradigms cannot be conflated. A more rarely studied phenomenon is the visual SL that is completely unsupervised and implicit. Several studies use visual stimuli, but in many cases, participants are hinted at a hidden pattern. Thus, the behavioral and neural background and its description is currently incomplete in the literature. We can derive several parameters about implicit visual SL from earlier studies.

The learning trajectory of visual SL has been described before. In this self-paced paradigm, they successfully described the learning curve of visual SL using two-alternative forced choice (2AFC) task with online, reaction time (RT) tracking. The exposure was not completely unsupervised, since participants were informed about the hidden pattern in the image sequence, yet it still provides useful information about the behavioral changes during the emergence of visual SL.

A completely implicit visual SL paradigm has been used before, which contributed both behavioral and neural data to the literature. This fMRI study used a picture sequence with faces and scenes. Participants were only instructed to categorize the appearing image with a button-press. Not revealed to the participants, the images formed associated stimulus pairs, that always followed each other in a fixed order. Thus, the second member of the image pairs became predictable. They found RT reduction for predictable images and an anticipatory effect. This anticipatory effect was a prolonged RT for the first member of the associated stimulus pairs. The examination of these effects was possible due to the introduction of so-called single images, which had no above-chance statistical relationship with preceding images, and they had no function in visual SL. They also confirmed the pair acquisition with an offline familiarity test after the stream exposure.

The image sequence, however, contained additional information above the associated pairs. Their image pairs were always formed using pictures for different categories (face-scene, scene-face). Thus, from the participants' point of view there was a greater chance that the next image will be of a different category. Besides, category repetition could only occur between a single condition and the first member of the pair. Since there was a smaller probability of category repetition, it could introduce a motor artefact that prolonged the RT of the first members.

Aims

Our goal was to examine unsupervised statistical learning with a visual sequence where an undisclosed, temporal regularity was placed into the stream. Reports were found to be either quasi-supervised or altered by higher level information. To do this we adapted and tested a previously reported unsupervised, visual SL paradigm. We examined the possible co-factors impacting the behavioral results and modified the paradigm to investigate the behavioral evidence for SL with an online RT test. The online paradigm also helps us not only to report the evidence for an SL effect, but also to describe the learning curve. The description of the SL trajectory further helps us to understand the complex network behind the cognitive process.

After establishing the behavioral parameters, we further adapted the paradigm to EEG. By recording cortical activity, we wanted to find possible differences, that are not only characteristics of SL but can also help us understand factors affecting the learning processes and possibly provide information about individual traits that influence SL.

Materials and methods

Behavioral study

Experiment 1a

In the first experiment we recreated the paradigm of Turk-Browne (2010) with different images. Thirty-eight volunteers (20 females, mean age: 25.34 y, range: 21-41 y) participated in Experiment 1a. All of them gave written informed consent; the study protocol was approved by the Human Investigation Review Board of University of Szeged (266/2017-SZTE). Five subjects were omitted from the analysis, due to their mean accuracies being under 60%.

For the stimuli of the experiment, we used gray-scale pictures of everyday objects which were selected from the Bank of Standardized Stimuli. A stream created from these images was presented to the volunteers. RT and accuracy were measured through 8 runs. In one run, the 8 images formed 4 associated image pairs, that always followed each other in the sequence. The rest of the four images served as control, so-called single images. Each image was presented 6 times to the participants. The image transition could fall under two definitions: category-repeating or category-alternating. These definitions mean that the leading and following images during transition belong to the same, repeating (Small-Small, Large-Large) or different, alternating categories (Large-Small, Small-Large). Experiment 1a only included category-alternating pairs.

Participants were asked to indicate the category (Small/Large) of the presented object with a button press. Participants were completely naïve to the sequence and the associated pairs. After 8 runs, participants were interviewed to see whether they recognized the pairs.

During data acquisition we recorded participants' answers and measured their RTs. Mean RTs in all three conditions were compared using one-way repeated measure ANOVA and later Tukey-Kramer test as pairwise *post hoc* analysis. For the accuracy data, Friedman test later Wilcoxon signed-rank test was used to compare the medians.

Every image was assigned a condition based on their location in the stream: P1, P2 and S. The first images of the stimulus pairs were labelled P1, second images P2 and the single images were labelled S. According to the hypothesis, P1 images induce anticipatory effect, while we should observe priming effects for P2 images. S images serve as control, so we can examine both anticipation and priming.

Experiment 1b

To check the assumed motor pattern in Experiment 1a, the pattern was modified in Experiment 1b to balance the category-alternating and category-repeating transitions in the sequence. Other parameters of the experiment were left unchanged.

Thirty-eight volunteers (18 females, mean age: 27.6y, range: 21-42y) participated in Experiment 1b. All of them gave written informed consent; the study protocol was approved by the Human Investigation Review Board of University of Szeged (266/2017-SZTE). We excluded 3 subjects due to poor performance.

Experiment 2

Based on Experiment 1a and 1b we made modifications to the paradigm. We changed the categorization task. We also increased the number of single stimuli in the stream, the number of participants, and the number of stimulus presentations as well to raise the effect size. To not lose the first trials an initial random sequence with the same stimuli was inserted at the beginning of the stream and a jittered intertrial interval (ITI) was introduced.

In Experiment 2, we had 87 healthy participants with correct or corrected-to-normal vision (48 females, mean age: 21.26y, range: 18-28y). All of them gave written informed consent; the study protocol was approved by the Human Investigation Review Board of University of Szeged (266/2017-SZTE). Due to low average accuracy, 4 participants were omitted from the analysis.

Sixteen images were selected for Experiment 2. Eight of these images were everyday objects, while the rest were images of animals. The first 10 presentations were the random stream, while the last 15 contained temporally associated stimulus pairs formed from the familiarized stimuli. The task was changed from categorization based on size to categorization based on whether it is an object or an animal. Participants had to answer with a button press on the numeric keyboard. Volunteers were interviewed afterwards with the same questions.

For the evaluation of the RT data, a linear mixed-effect model with restricted maximum likelihood criterion was implemented. Fixed effect was evaluated using type III ANOVA. Satterthwaite's method was used to obtain degrees of freedom and p values. *Post hoc* analysis included the estimated marginal means with Tukey correction. The interaction was evaluated using the estimated marginal means of linear trend with Tukey correction.

A generalized linear mixed-effect model with binomial distribution was fit to evaluate the accuracy data. To test the fixed effects, we used type III Wald χ^2 test.

EEG study

We adapted our paradigm to EEG. This included abandoning the categorization task and online monitoring of SL and changing it to the offline familiarity test. To confirm the adapted paradigm, we conducted a pilot behavior study.

In the pilot study we had 17 participants (9 females, mean age: 25.7y, range: 20–26y), while we recorded the EEG data of 30 participants (16 females, mean age: 26.4y, range: 21–37y). All participants provided written, informed consent. One participant was excluded from the latter analysis due to poor signal-to-noise ratio. The study protocol was approved by the Human Investigation Review Board of the University of Szeged (266/2017-SZTE).

All participants were exposed to 3 runs of image sequences. One run was made up of 25 presentations of 16 images of everyday objects. Twelve images of animals were inserted into the stream randomly as detection task to maintain the attention level of the participants. The first 10 presentations of the images were random, while the last 15 contained the image pairs. To evaluate the regularity acquisition participants performed an offline, familiarity test after the presentation of the sequences. The test was a subject-paced 2AFC design with a total of 32 presentations of stimulus pairs.

For the recordings, a 64-channel Biosemi Active II system was used. Preprocessing was carried out in EEGLAB, MATLAB, while further analysis in Fieldtrip, MATLAB. Event-related potential (ERP), time-frequency (TF) and intertrial phase coherence (ITPC) analysis was performed.

The data of the familiarity test was first converted into sensitivity (A') according to the modified Grier's formula, then it was tested against 0.5 with one sided t-test. Additionally, we used it to divide participants into two groups: chance performers (C, $A' \leq 0.5$), and above-chance (AC, $A' > 0.5$) performers.

ERPs between conditions were compared using permutation statistics with cluster-based correction. After acquiring TF data with Morlet wavelet, we determined a window of interest, based on the visual inspection of the averaged data. The mean power of this window was correlated with subjects' A' value using Pearson's correlation. Afterwards, the power in the TF window was compared between the AC and C groups and between conditions to determine the scalp distribution of the activity. In both cases permutation statistics with cluster-based correction was used. Lastly, the ITPC values in the TF window of interest were compared against a same size window in the prestimulus baseline period using Wilcoxon sign rank test due to the non-normal distribution of the data.

Results

Behavioral study

Experiment 1a

Analyzing the RT data of the different conditions showed a great effect in the learning paradigm ($F(2,64)=10.002$, $p<0.001$). Pairwise comparison of the three conditions revealed a priming effect on condition P2 (mean=0.592 s, SD=0.123 s) as its mean RT was lower than both Condition P1 (mean=0.614 s, SD=0.133 s, $q=3.94$, $p=0.001$) and Condition S (mean=0.611 s, SD=0.133 s, $q=3.484$, $p=0.004$). We could not detect a significant difference between the RT of Condition P1, and S. Accuracy data also showed the priming effect ($n=33$, $\chi^2=20.33$, $p<0.001$). *Post hoc* analysis showed that Condition P2 (median=0.95, IQR=0.063) has a higher accuracy than P1 (median=0.931, IQR=0.086, $z=-3.45$, $p<0.001$) and S (median=0.919, IQR=0.070, $z=-3.806$, $p<0.001$).

An additional analysis was conducted where we removed the trials where the previous image belonged to the same category. The RT of Condition P2 (mean=0.592 s, SD=0.119 s) did not differ significantly from either Condition P1 (mean=0.595 s, SD=0.112 s) or Condition S (mean=0.594 s, SD=0.132 s) using repeated measure ANOVA ($F(2,64)=0.145$, $p=0.866$). The effect size of the accuracy showed the same tendency, where the significant difference disappeared ($n=33$, $\chi^2=0.14$, $p=0.934$) between the three conditions (P1: median=0.942, IQR=0.084; P2: median=0.95, IQR=0.064; S: median=0.94, IQR=0.057).

Experiment 1b

ANOVA revealed a tendency in the RT data ($F(2,68)=2.458$, $p=0.093$) between the three conditions (P1: mean=0.618 s, SD=0.097 s; P2: mean=0.611 s, SD=0.097 s; S: mean=0.617 s, SD=0.097 s). The accuracy data did not show a significant effect either ($n=35$, $\chi^2=0.41$, $p=0.814$; P1: median=0.944, IQR=0.064; P2: median=0.95, IQR=0.052; S: median=0.944, IQR=0.064).

Comparing the results of Experiment 1a and 1b

Holm-Bonferroni corrected t-test showed tendency ($t(66)=2.083$, $p=0.082$) in the RT difference between Condition P2 and S in Experiment 1a (mean=0.019 s, SD=0.031 s) and Experiment 1b

(mean=0.006 s, SD=0.019 s), while Holm-Bonferroni corrected Mann-Whitney U test revealed a significant difference ($z=-2.56$, $p=0.0315$) in the accuracy data between Experiment 1a (median=-0.025, IQR=0.028) and Experiment 1b (median=0.0, IQR=0.044).

The difference between Condition P1 and P2 also showed a tendentious change ($t(66)=2.421$, $p=0.054$) in the RTs of Experiment 1a (mean=0.022 s, SD=0.032 s) and Experiment 1b (mean=0.006 s, SD=0.021 s). The accuracy difference appeared to be significant between the two experiments ($z=-2.33$, $p=0.039$; Experiment 1a: median=-0.025, IQR=0.052; Experiment 1b: median=0.0, IQR=0.061). Condition P1 and S difference did not show a change in either RT or accuracy data.

Experiment 2

The mixed model did not detect a significant effect on the accuracy by any of the investigated variables (repetition: $\chi^2=1.949$, $df=1$, $p=0.163$; condition: $\chi^2=2.308$, $df=2$, $p=0.315$; interaction: $\chi^2=1.237$, $df=1$, $p=0.539$) except for the effect of the ITI ($\chi^2=14.936$, $df=1$, $p<0.001$).

The model fitted to the RT data revealed significant effects such as the condition ($F(2,38030)=3.344$, $p=0.035$), the interaction of the $\log(\text{repetition number}) \times \text{condition}$ ($F(2,38048)=4.303$, $p=0.014$) and the ITI ($F(1,38048)=407.456$, $p<0.001$). We performed a *post hoc* pairwise comparisons for the categorical significant effects. Comparing the linear trends of the repetition and condition interaction revealed that P2 and S slopes are significantly different ($z=2.856$, $p=0.012$) while P1 and P2 showed tendency ($z=2.195$, $p=0.072$).

In the next step of the analysis, we examined the RT difference slope of Conditions S and P2. This data was fitted to linear regression model as a function of the repetition number. To test the hypothesis that the emergence of the behavioral evidence shows a logarithmic trajectory we fitted two models: Model A, with a linear predictor variable and Model B with a logarithmic predictor variable. Both Model A ($R^2=0.005$, $F(1,1243)=6.926$, $p=0.012$) and Model B ($R^2=0.008$, $F(1,1243)=9.767$, $p=0.002$) achieved significance. To compare the models, we used encompassing test (lmtest package, R). Model A reached significance in the encompassing test ($F(-1,1242)=4.984$, $p=0.026$), while model B did not ($F(-1,1242)=1.528$, $p=0.217$).

EEG study

Testing participants A' values (mean=0.6, SD=0.17) confirmed that the sample mean is significantly above 0.5 ($t(16)=2.44$, $p=0.0132$) in the pilot study. Based on this result, we utilized the adapted paradigm and recorded EEG.

During the EEG study, mean A' was above 0.5 (mean=0.53, SD=0.18), however it did not reach significance ($t(28)=1.002$, $p=0.162$). The performance of the familiarity test in latter analysis was used to divide participants into two groups: group AC and group C.

First, we determined a window of interest, by averaging the trials together over subjects, conditions, and channels. Based on the visual inspection of the averaged data, we defined a time-frequency window of interest between 40-70 Hz and 0.5-0.75 s post stimulus.

After establishing the window, we investigated the relationship between the neural data and the behavioral performance. The average power within the time window showed a positive correlation with the participants' A' values ($n=29$, $r=0.371$, $p=0.048$).

Next, we compared the AC and C groups to see whether they differ and what scalp distribution they exhibit. Permutation statistics revealed an emerging cluster in the average power of the TF window appearing in the left frontoparietal region ($t_{\text{sum}}=860.57$, $p=0.041$). The AC group exhibited higher gamma power (mean=0.35 dB, SEM=0.07 dB), than the C group (mean=0.08 dB, SEM=0.05 dB).

After determining the scalp distribution of the post stimulus gamma difference, we examined if this activity is whether condition specific. We compared the different conditions (P1, P2 and S) including all subjects first. This analysis did not yield any results as no significant cluster emerged on the scalp. In the next step we compared the condition within the AC and C group separately. The C group again, did not show the appearance of any channel cluster. In the AC group a cluster emerged in the left frontoparietal area ($t_{\text{sum}}=681.3$, $p=0.021$) when comparing Condition P1 and S.

As the last step, we examined if the gamma activity is phase-locked to the stimulus presentation and performed ITPC analysis in Condition P1 of the AC group and it was compared to a prestimulus baseline window (-0.4 - -0.15 s, 40-70 Hz) in the same group and condition. The ITPC of the AC group (median=0.07, IQR=0.005) did not show significant difference ($n=14$, $z=-0.282$, $p=0.78$) comparing it against the prestimulus window (median=0.068, IQR=0.005).

Discussion

Behavioral study

The aim of the present study was to observe the effects in an unsupervised visual SL paradigm: priming and anticipatory effects. We used a modified version of a formerly utilized paradigm in Experiment 1a and replicated their results of reduced RT and greater accuracy for the predictable member of temporally associated image pairs which led to the conclusion of a priming effect, however we could not find any evidence for an anticipatory effect.

Experiment 1a only contained category-alternating associated pairs. This resulted in the fact that the majority of the image transitions became category-alternating. Furthermore, the smaller chance of category-repeating transitions and thus the violation of the statistical motor information can only occur in Condition P1 and S. The appearance of unexpected stimuli can lead to greater RT, and this further increases the RT difference between category-repeating and category-alternating transitions. This is a form of implicit learning as well, however it cannot be specified as visual SL since the acquired information is not visual but rather motor response. The parallel categorization task and motor responses biased the outcome of the experiment which was proved by a reanalysis of the data of Experiment 1a and the follow-up measurement in Experiment 1b. We reduced the motor pattern by the introduction of category-repeating stimulus pairs, and we experienced a drastic drop in the priming effect size, nevertheless the statistical regularity remained unchanged in the image sequence.

We set out to modify this paradigm in a way that shows the behavioral remarks of visual SL without underlying motor components. First, we raised the number of subjects and the number stimulus presentation to boost the effect size. We also changed the categorization task to be more straightforward. The variance in the RT data and its curve called for the need of insertion a warm-up period. To reduce the monotone pace of the task random ITI was introduced in the sequence. The modified paradigm appeared as an effective tool to observe behavioral aspects of visual SL, since we detected condition specific RT changes and managed to characterize the learning curve.

The analysis of RT data of Experiment 2 revealed the emergence of the priming effect through the changes in the linear trends. Besides, the learning trajectory showed a rather logarithmic curve. This implies the relatively rapid development of SL effect additionally to the evidence, that the number of regularity presentation in the experiments were low compared to other studies.

EEG study

Though the familiarity test of the EEG study did not yield significant results, the results of the pilot study provided us evidence that the paradigm is adequate to prompt learning effects. Despite the nonsignificant results of the familiarity test during the EEG recording, the electrophysiological data cannot be diminished because as discussed before, unsupervised SL utilizes implicit systems while the familiarity test requires explicit knowledge.

The EEG results consist of high frequency oscillation 0.5-0.75 s after post stimulus, which does not appear to be phase-locked to the image presentation. This activity also showed a positive correlation with the behaviors findings and emerged in the frontoparietal region of the scalp. The frequency, spatial and temporal properties of the observed gamma activity led us to the deduction that this condition specific oscillatory change represents model-based learning described in model-free and model-based learning theory. Stimulus-driven model-free learning is responsible for the extraction and acquisition of environmental stimulus-patterns and regularities. It is hypothesized as a function utilizing bottom-up processes and it is tied to the posterior areas of the brain. Parallely, model-based learning is a rather top-down process, that makes use of the already collected information and construct a model, an internal representation of the environment. Model-based learning applies the model to adjust cortical function and achieve higher performance, overall leading to a goal-oriented behavior. These processes have been tied to frontal regions, like the dorsolateral prefrontal cortex. This observation related to explicit processes is valuable, but it does not paint a full picture. Associating frontal gamma activity with explicit knowledge and model-based learning, it does not fully explain the neurological background of the SL variance due to the definition of model-based learning. It involves several cognitive functions (e.g. attention, mnemonic processes, decision-making), thus it does not give a definitive answer. Attention could be a great candidate that would explain the differences experienced here and previously. The performance for attended and unattended stimuli has been observed, where attended stimuli resulted in greater behavioral performance. Attention is also essential for the formation of explicit memory, which the familiarity test requires. Future goals involve the systematic investigation of the gamma-band and identification of its source and exact role it plays in the process of SL. Identifying this component helps us understand the neural background and better investigate its function in perception and cognition.

Conclusion

In the presented studies we explored the behavioral and cortical aspects of the unsupervised acquisition of temporally associated visual stimuli. We adapted a previously published paradigm that utilizes stimulus pairs and recorded participants' answers and RTs. We recreated their results and found that predictable stimuli elicited higher accuracies and lower RT. Following these observations, we modified the design to eliminate a suspected motor pattern in the stream. The modified paradigm with the same statistical regularity but lower amount of motor information yielded considerably smaller effects sizes. The individual results of Experiment 1a and 1b and their direct comparison led us to the conclusion that the original design and its results are skewed and do not reflect a reliable SL effect. Subsequently to this remark, we set our goals to modify the design and increase the SL effect. We managed to observe the reduction of RT and negative linear trend for predictable images without the motor pattern this time. Moreover, we could describe the learning trajectory based on the RT difference of the predictable and control images. The curve showed a logarithmic trajectory which is in line with previous findings.

After establishing the behavioral aspect of unsupervised VSL, we shifted our attention toward the cortical activities associated with SL. We adapted the design to be suitable for EEG recording. A window of interest emerged in the gamma range (40-70 Hz) 0.5-0.75 s after stimulus presentation. The average power within the window showed a positive correlation with the results of the familiarity test. Data showed that the gamma activity spread across the frontoparietal area with a greater expanse in the frontal region.

The spatial and temporal distribution of the observed activity showed a great similarity with the model-based learning processes. These cortical functions are described as top-down mechanisms that control our attention, decision making and overall create goal-oriented behavior. These activities are part of a greater cortical network, called frontoparietal network. Previous results and our findings suggest that the posterior part of this network is responsible for the mostly stimulus-driven, bottom-up processes of learning that contribute towards the implicit knowledge of environmental regularity. The anterior areas are responsible for the goal-oriented top-down behavior, that modulates other cognitive functions based on the previously acquired information.

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