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# Hidden Markov Models for Visual Processing of Marketing Leaflets

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**Abstract.** The study shows the application of hidden Markov models (HMMs) for the analysis of eye ball movement fixations. The registered visual activity concerns pairwise comparisons of simple advertisement leaflets, differed in their layout orientation and captions' styles. A simulation experiment was conducted to specify the most appropriate HMMs in terms of information criteria. Six best models were discussed in detail. The identified hidden states together with transition and emission probabilities were the basis of subjects' visual behavior hypothetical interpretations.

**Keywords:** eye tracking · cognitive modeling · visual presentation · digital signage · advertisement · human factors · ergonomics

## 1 Introduction

Processing visual information by human beings is a crucial activity that accompanies the variety of peoples' everyday tasks. Understanding how people examine graphical features broadens our knowledge and leads to practical ergonomic recommendations. Eye-tracking is one of the methods that allows for the investigation of visual behavior in an objective way and is widely used by researchers in various areas (e.g., [3], [9], [13], [16]). For the review see, for example, Huddleston et al. [7]. The direct examination of eye movement data refers to the so-called overt attention [4]. Covert attention may be studied by applying more sophisticated mathematical approaches such as Markov models. The general goal of the present study is to extend our knowledge about visual processing of simple advertisement leaflets by taking advantage of hidden Markov models (HMMs). The approach focuses on states and probabilities of shifting between them. These parameters are estimated based on fixation sequences registered in specified areas of interests (AOIs). The paper is a continuation of the trend of research presented in, e.g., [5], [6], [16].

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## 2 Overview of the Experiment

The current paper analyses are based on the eye-tracking data presented in the research of Michalski and Biazik [11]. The experiment investigated visual marketing information subjective assessments. The study involved four digital versions of advertising leaflets differed in the orientation (vertical or horizontal layouts) and style - bolded or normal font types of captions. All experimental conditions were evaluated by binary pairwise comparisons. Each subject tested all six possible pairs of stimuli. The data were gathered in a separated room with typical office equipment and 21" computer screen. A stationary, infrared eye-tracker (SMI RED500) was employed to register eye-balls movements at 500Hz frequency. The accuracy of the system amounts to  $0.4^\circ$ . Fixations' locations, recorded from 33 males and 16 females, aged between 19 and 31 years (average: 21.9 and standard deviation of 3.0.) were used in further examinations in the present paper. The obtained results showed that variants with bolded captions are better perceived than those with normal ones. Additionally, subjects preferred horizontal layouts to their vertical equivalents. The final hierarchy of preferences determined by calculating selection percentages was as follows: horizontal & bolded = 43%, vertical & bolded = 30%, horizontal & normal = 21%, vertical & normal = 7%.

## 3 Hidden Markov Models

Though Markov models are known since 1913 [8], their applications to visual information processing is rather scarce. In the current study, a discrete, first-order HMMs are employed for modelling of fixations data changes while doing the preference assessments tasks. Based on fixation sequences registered by the eye-tracker, we identify hidden states, states' transition probability matrix  $A$ , emission probabilities matrix  $B$ , and the starting likelihoods  $\pi$ . These, in turn, are used to model visual attention shifts. More details about this approach can be found in multiple publications. For instance, Rabiner [14] presents mathematical foundations of HMMs and their possible applications in various areas. A number of distinct areas of interests (AOIs) were specified for all examined conditions. A sample is presented in Fig. 1. Fixations' sequences and the defined AOIs were used for derivation of HMMs' parameters ( $A$ ,  $B$ ,  $\pi$ ).

Title		Nasi specjaliści	
Ortopedzi:	O_Title	Fizjoterapeuci:	F_Title
dr n. med. Dorota Kozłowska	O_Content	dr Piotr Duda	F_Content
dr n. med. Kacper Górniak		mgr Krzysztof Markowski	
lek. med. Jaromir Leszczyński		mgr Iwona Malicka	

Fig. 1. Defined AOIs for a sample stimulus (horizontal orientation and bolded header style)

TIBCO Statistica along with SMI BeGaze software were used to process eye ball movements data. HMMs' probabilities were obtained by the Baum-Welch procedure [2], implemented by Murphy [12]. The number of iterations was set at 1000, whereas the convergence threshold amounted to 0.0001. The computations were performed in Matlab.

**Table 1.** The HMM simulation results for all comparisons. Smaller values of AIC and BIC correspond to better models. Values in brackets denote standard deviations, V=Vertical, H=Horizontal layouts; N=Normal, B=Bolded captions' fonts.

No	Comparison	No of states	AIC		BIC		Log-likelihood	
			Mean	Min	Mean	Min	Mean	Max
1.	<b>1.</b>	2	3770 (97)	2312	2454	2424	-1145	-1130
2.		3	3671 (31)	2285	2492	2467	-1113	-1101
3.	<b>V_N ↔ H_N</b>	<b>4</b>	3605 (44)	<b>2269</b>	2561	2529	-1091	-1075
4.		5	3554 (50)	2272	2639	2618	-1066	-1056
5.		6	3528 (41)	2285	2751	2727	-1053	-1041
6.	<b>2.</b>	2	4485 (106)	2009	2131	2118	-985	-978
7.		3	4351 (70)	1984	2178	2161	-959	-950
8.	<b>V_N ↔ V_B</b>	<b>4</b>	4262 (64)	<b>1970</b>	2243	2222	-936	-925
9.		5	4223 (49)	1972	2332	2308	-918	-906
10.		6	4200 (44)	1987	2439	2415	-903	-891
11.	<b>3.</b>	2	3892 (79)	2391	2521	2504	-1178	-1170
12.		3	3727 (45)	2355	2552	2537	-1143	-1135
13.	<b>H_N ↔ H_B</b>	<b>4</b>	3684 (28)	<b>2338</b>	2621	2599	-1120	-1109
14.		5	3656 (27)	2351	2715	2699	-1103	-1096
15.		6	3648 (25)	2364	2827	2808	-1090	-1080
16.	<b>4.</b>	2	4294 (105)	1888	2025	1996	-933	-918
17.		<b>3</b>	4150 (57)	<b>1854</b>	2051	2029	-896	-885
18.	<b>V_N ↔ H_B</b>	<b>4</b>	4070 (39)	<b>1854</b>	2124	2103	-877	-867
19.		5	4028 (36)	1865	2217	2197	-863	-852
20.		6	4019 (38)	1894	2331	2317	-852	-845
21.	<b>5.</b>	2	3983 (113)	2708	2873	2824	-1352	-1328
22.		3	3745 (67)	2676	2903	2864	-1315	-1296
23.	<b>V_B ↔ H_N</b>	4	3671 (65)	2672	2972	2941	-1292	-1276
24.		<b>5</b>	3622 (44)	<b>2667</b>	3059	3025	-1271	-1254
25.		6	3607 (37)	2677	3165	3134	-1252	-1237
26.	<b>6.</b>	2	3777 (86)	2424	2559	2537	-1197	-1186
27.		3	3654 (61)	2368	2570	2551	-1151	-1142
28.	<b>V_B ↔ H_B</b>	4	3583 (29)	2347	2632	2608	-1125	-1113
29.		<b>5</b>	3548 (41)	<b>2331</b>	2713	2680	-1102	-1086
30.		6	3536 (31)	2341	2811	2785	-1081	-1068

While using HMMs, one of the most important problems is the determination of the most suitable number of hidden states. To this end, a simulation experiment was performed.

It included 30 conditions resulting from 6 comparisons from the investigation and 5 numbers of hidden states (from 2 to 6). One hundred simulations were conducted for each condition to minimize the influence of initial values on final estimations. The Akaike's Information Criterion (AIC) [1], Bayesian Information Criterion (BIC) [15] together with log-likelihood values were used to evaluate the quality of the results (Table 1).

The examination of the experimental simulation results shows that for comparisons 1, 2, and 3, four-states models are the best. In the case of comparison 4, a three-states solution is the most suitable, whereas for the remaining 5<sup>th</sup> and 6<sup>th</sup> comparisons, the five-states HMMs are the most appropriate. These best solutions according to AICs are presented in detail in Tables 2–7, and further analyzed in next paragraphs. Tables including HMMs' estimates are divided generally into three sections. The second rows include initial states probabilities ( $\pi$ ), next 3, 4, or 5 rows present between-states transition probabilities ( $A$ ), whereas subsequent rows contain emission probabilities ( $B$ ). The AOI acronyms were prepared in the following rules: L, R = Left or Right location on the screen; V, H, N, B as in the caption from Table 1; M, O, F = Main, Ortodonta, Fizjoterapeuta; T, C = Title, Content.

**Table 2.** Four (4) states HMMs for the (1) first comparison

	S1	S2	S3	S4
$\pi$	<b>0.89</b>	0.09	0.01	0.00
S1	<b>0.53</b>	<b>0.31</b>	0.00	0.12
S2	<b>0.27</b>	<b>0.61</b>	0.07	0.00
S3	0.09	0.08	<b>0.74</b>	<b>0.22</b>
S4	0.11	0.00	<b>0.19</b>	<b>0.66</b>
[1]: L_V_N_M_T	<b>0.30</b>	0.02	0.00	0.00
[2]: L_V_N_O_T	<b>0.33</b>	0.00	0.02	0.12
[3]: L_V_N_O_C	0.13	0.00	0.00	<b>0.51</b>
[4]: L_V_N_F_T	0.00	0.00	0.01	<b>0.32</b>
[5]: L_V_N_F_C	0.00	0.00	0.00	0.06
[6]: R_H_N_M_T	0.01	<b>0.55</b>	0.00	0.00
[7]: R_H_N_O_T	0.13	<b>0.33</b>	<b>0.18</b>	0.00
[8]: R_H_N_O_C	0.09	0.02	<b>0.51</b>	0.00
[9]: R_H_N_F_T	0.00	0.08	0.10	0.00
[10]: R_H_N_F_C	0.00	0.00	<b>0.17</b>	0.00

**Table 3.** Four (4) states HMMs for the (2) second comparison

	S1	S2	S3	S4
$\pi$	<b>0.71</b>	0.14	0.09	0.06
S1	<b>0.55</b>	<b>0.21</b>	0.00	0.00
S2	<b>0.28</b>	<b>0.49</b>	0.00	<b>0.16</b>
S3	0.14	0.00	<b>0.60</b>	0.05
S4	0.04	<b>0.30</b>	<b>0.40</b>	<b>0.79</b>
[1]: L_V_N_M_T	<b>0.40</b>	0.04	0.00	0.00
[2]: L_V_N_O_T	<b>0.41</b>	0.00	0.02	0.01
[3]: L_V_N_O_C	0.12	0.00	<b>0.47</b>	0.11
[4]: L_V_N_F_T	0.00	0.00	<b>0.29</b>	0.00
[5]: L_V_N_F_C	0.00	0.00	<b>0.19</b>	0.01
[6]: R_V_B_M_T	0.00	<b>0.41</b>	0.00	0.00
[7]: R_V_B_O_T	0.05	<b>0.35</b>	0.01	0.04
[8]: R_V_B_O_C	0.02	<b>0.20</b>	0.00	<b>0.49</b>
[9]: R_V_B_F_T	0.00	0.00	0.03	<b>0.26</b>
[10]: R_V_B_F_C	0.00	0.00	0.00	0.08

Even the cursory analysis of the presented models shows their far-reaching variability. The number of hidden states differs from 3 to 5, thus, the rational interpretation is not straightforward. The detailed examination, however, indicates that the obtained models are highly sensitive to key factors characteristic of individual comparisons and subjects' preferences towards examined stimuli. The number of hidden states seems to be related with the degree of difference between declared preferences. For instance, 3 states model that appears in comparison 4 includes the best and the worst rated variants. The difference amounts as much as 36%. The biggest number of states, in turn, is assigned for comparisons 5 and 6, where the difference in preferences' evaluation equals merely 8%

and 7%, respectively. In tasks 1, 2, and 3, where 4-state models are recommended, these differences are 14%, 23%, and 22%, respectively.

**Table 4.** Four (4) states HMMs for the (3) third comparison

	S1	S2	S3	S4
$\pi$	<b>0.78</b>	0.20	0.02	0.00
S1	<b>0.58</b>	0.00	0.06	0.06
S2	<b>0.12</b>	<b>0.63</b>	<b>0.19</b>	0.00
S3	0.00	<b>0.24</b>	<b>0.66</b>	<b>0.26</b>
S4	<b>0.29</b>	<b>0.13</b>	0.09	<b>0.67</b>
[1]: L_H_N_M_T	<b>0.54</b>	0.00	0.00	0.07
[2]: L_H_N_O_T	<b>0.17</b>	<b>0.21</b>	0.05	0.00
[3]: L_H_N_O_C	0.00	<b>0.19</b>	0.00	0.00
[4]: L_H_N_F_T	0.10	<b>0.18</b>	0.02	0.05
[5]: L_H_N_F_C	0.00	<b>0.32</b>	0.00	0.00
[6]: R_H_B_M_T	0.07	0.00	0.00	<b>0.39</b>
[7]: R_H_B_O_T	0.11	0.02	<b>0.31</b>	<b>0.29</b>
[8]: R_H_B_O_C	0.00	0.08	<b>0.51</b>	0.00
[9]: R_H_B_F_T	0.00	0.00	0.01	<b>0.19</b>
[10]:R_H_B_F_C	0.00	0.00	0.10	0.00

**Table 5.** Three (3) states HMMs for the (4) fourth comparison

	S1	S2	S3
$\pi$	<b>0.56</b>	0.44	0.00
S1	<b>0.82</b>	0.05	0.01
S2	<b>0.17</b>	<b>0.67</b>	<b>0.09</b>
S3	0.00	<b>0.28</b>	<b>0.90</b>
[1]: L_V_N_M_T	<b>0.27</b>	0.02	0.00
[2]: L_V_N_O_T	0.09	<b>0.29</b>	0.00
[3]: L_V_N_O_C	0.03	<b>0.36</b>	0.00
[4]: L_V_N_F_T	0.00	0.08	0.00
[5]: L_V_N_F_C	0.00	0.05	0.00
[6]: R_H_B_M_T	<b>0.24</b>	0.00	0.07
[7]: R_H_B_O_T	<b>0.26</b>	0.03	<b>0.26</b>
[8]: R_H_B_O_C	0.06	0.16	<b>0.48</b>
[9]: R_H_B_F_T	0.05	0.00	0.06
[10]:R_H_B_F_C	0.00	0.00	0.13

**Table 6.** Five (5) states HMMs for the (5) fifth comparison

	S1	S2	S3	S4	S5
$\pi$	<b>0.51</b>	0.17	0.15	0.13	0.03
S1	<b>0.57</b>	<b>0.34</b>	0.00	0.10	0.14
S2	0.00	<b>0.48</b>	<b>0.80</b>	<b>0.29</b>	0.00
S3	<b>0.30</b>	0.00	0.00	0.00	0.11
S4	0.00	0.09	<b>0.19</b>	<b>0.53</b>	<b>0.16</b>
S5	<b>0.13</b>	0.09	0.00	0.08	<b>0.59</b>
[1]: L_V_B_M_T	<b>0.33</b>	0.00	0.13	0.00	0.01
[2]: L_V_B_O_T	<b>0.40</b>	0.00	0.11	0.02	0.01
[3]: L_V_B_O_C	<b>0.27</b>	0.00	<b>0.18</b>	0.00	<b>0.45</b>
[4]: L_V_B_F_T	0.00	0.00	0.00	0.00	<b>0.38</b>
[5]: L_V_B_F_C	0.00	0.00	0.01	0.00	<b>0.15</b>
[6]: R_H_N_M_T	0.00	<b>0.46</b>	<b>0.21</b>	0.00	0.00
[7]: R_H_N_O_T	0.00	<b>0.37</b>	<b>0.31</b>	0.02	0.00
[8]: R_H_N_O_C	0.00	0.00	0.06	<b>0.81</b>	0.00
[9]: R_H_N_F_T	0.00	0.16	0.00	0.02	0.00
[10]:R_H_N_F_C	0.00	0.00	0.00	<b>0.14</b>	0.00

**Table 7.** Five (5) states HMMs for the (6) sixth comparison

	S1	S2	S3	S4	S5
$\pi$	<b>0.65</b>	0.21	0.15	0.00	0.00
S1	<b>0.57</b>	0.00	<b>0.31</b>	0.00	0.00
S2	0.10	<b>0.27</b>	0.00	<b>0.46</b>	0.00
S3	0.07	<b>0.52</b>	<b>0.64</b>	0.00	0.00
S4	<b>0.26</b>	0.00	0.00	<b>0.53</b>	<b>0.21</b>
S5	0.00	<b>0.21</b>	0.05	0.00	<b>0.79</b>
[1]: L_V_B_M_T	<b>0.25</b>	0.07	0.00	0.00	0.00
[2]: L_V_B_O_T	<b>0.32</b>	0.00	0.01	0.13	0.00
[3]: L_V_B_O_C	<b>0.30</b>	0.00	0.00	<b>0.45</b>	0.00
[4]: L_V_B_F_T	0.00	0.00	0.00	<b>0.33</b>	0.00
[5]: L_V_B_F_C	0.00	0.03	0.00	0.09	0.07
[6]: R_H_B_M_T	0.00	0.00	<b>0.50</b>	0.00	0.00
[7]: R_H_B_O_T	0.04	<b>0.41</b>	<b>0.27</b>	0.00	0.11
[8]: R_H_B_O_C	0.09	<b>0.50</b>	0.03	0.00	<b>0.41</b>
[9]: R_H_B_F_T	0.00	0.00	<b>0.17</b>	0.00	0.06
[10]:R_H_B_F_C	0.00	0.00	0.01	0.00	<b>0.35</b>

Moreover, one may notice that in models for comparisons 2 and 3, one of the states occurs very rarely: S3 for comparison 2 and S4 for the third model. This may suggest

that these cases are rather closer to the 3-state than 5-state proposals. Though the interpretation of the hidden states can be formulated as “the analysis either upper or lower part of the leaflet performed individually for left- or right hand side located variant”, the visual strategies are diverse.

In comparisons with the smallest preferences’ differences (5 and 6) the states’ sequence corresponds to the analysis of upper parts of leaflets positioned on the left and right first, and then the examination of lower parts of variants, that is, M, OT, OC AOIs. Next, states responsible for generating considerable emission probabilities for bottom AOIs are activated. There is also an alternative strategy observed which occurs less frequently. First, the analysis of the whole left variant (top and bottom) is performed and then, the exploration of the leaflet situated on the right hand side takes place.

In comparisons 2 and 3 with 23% and 22% of preferences’ differences, visual analysis strategies of exploring upper and lower leaflets’ parts are clear. For task 2:  $S1 \rightarrow S2 \rightarrow S4 \rightarrow S3$  whereas for task 3:  $S1 \rightarrow S4 \rightarrow S3 \rightarrow S2$ . For a model corresponding to the biggest preference variability (comparison 4), the hidden states have different features. S1 and S2 can be interpreted as “the comparative analysis of the upper and lower parts of both variants, respectively”. State S3 corresponds to the detailed analysis of the right leaflet bottom section, which was rated the best by participants. It seems that S3 may be related with seeking the confirmation of the right variant predominance. Similar phenomenon of detailed examination of more preferred leaflets exists in all comparisons from 1 to 6 (S3, S4, S3, S3, S5, S5, respectively).

## 4 Discussion and Conclusion

Presented in this paper HMMs for visual activity registered while performing binary pairwise comparisons of simple advertisement leaflets are promising. Discussed models and their properties have a potential to be more widely used in visual activity research. Obtained in this way knowledge could be taken advantage of in the design of visual information systems. It seems that demonstrated relations between the complexity of objects’ pairwise evaluation tasks and applied visual strategies may be especially useful in future studies and practical applications.

The decreasing number of hidden states along with the increase in diversity between examined variants, provides the perspective for the development of tools for automatic evaluation of the visual tasks’ difficulty. Moreover, the phenomenon of detailed examination of more preferred leaflets could possibly be used for the automatic detection of the visual communication design quality level.

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