Utilizing and modeling of gaze distribution in commercial eye-tracking research

Visual systems, final paper

Mgr. Jeroným Klimeš, Ph.D.

2003

1. Introduction

Commercial use of eye tracking is quickly developing branch of marketing psychology. It has clear practical aim: Understand consumer behavior on some advertising material, and this way to enhance sale rate and profit. Even this very straightforward goal demands a good understating of underlying perceptual processes and solving of many ongoing questions.

Let's demonstrate the question on an example from praxis. We have two materials that are almost identical in content (text and tables) but strikingly different in appearance (see picture bellow). The first, old one is just plain black and white output from a laser printer. The second, new one is colorful cut of cardstock leaflet. The question for a manufacturer is of course what is the difference between these two versions in effect at a customer, as there is a big difference in historical costs. (The old one is of course much cheaper.) So the primary questions on a researcher are: When we are to use old version, when a new one? For what sort of customers is this or that version better? Are the manufacturers just wasting money by making a nice leaflet that goes immediately into a trashcan?

It is clear from these questions, that there is firmly given unit of research in commercial research. It is an advertisement, a flyer, a leaflet, a mailing, a picture of a product in a catalogue, etc. These units as stimuli are usually very complex and researchers have only sometimes possibility to compare two versions of the given material. The information about the unit must be derived from how a test person observed the presented material. A lot of effort is therefore oriented to first describe and afterwards to categorizes different ways of processing of the scoped material.

A basic methodological tool is object coding. The material is divided to parts of interest, so called codes, and a video recording with gaze information is afterwards manually coded into a database of sequential codes. Duration of a particular gaze is afterwards computed from this:

Onset time [s]	**Observed element - code**	**computed gaze duration [s]**
0.00	Non defined objects	17.24
17.24	Picture of product #1	0.28
17.52	Picture of product #2	0.32
17.84	Fault – missing signal of eye position	0.16
18.00	Picture of product #2	1.16
...		

Table – Example of a database of codes

Source database of one test person consist of codes for areas of interest (here pictures of products) and supplementary codes. First of all, a collective code for all objects out of scope of interest (so called Nondef), and a code for intervals where eye-tracker does not transmit the signal on eye position (so called Fault). The step and minimal possible increment in this case was a single frame of videosequence, i.e. 0.04 second.

From the example of the database, it is clear that a gaze can consist of single saccade or fixation, but it is a collection of huge number of fixations and saccades in most cases. The recording is usually analyzed by coding step (0.04 – 2 s), what is minimal duration of a gaze and minimal gaze increment at the same time, and there are a few rules how define size of coding step to ensure necessary precision.

This database serves for many purposes. First of all for descriptive characteristic of the material – total time spent per code, relative time per code and square, seen, i.e. visible and invisible parts of the material etc. A lot of information is though lost by this approach. So there are attempts to derive more information about the material by analyzing just the distribution of code's duration.

Duration of a gaze depends on many factors. In the short time scale (< 0.5 s), it is influenced by distribution between fixations and saccades. Reading processes start at time of seconds. At long times (~60 s), duration of a code is influenced by higher strategies, say satiety time constant which prevent a person from wasting of time. So that a distribution of code's duration is clearly not normal, and it is rather combination of more contributing factors.

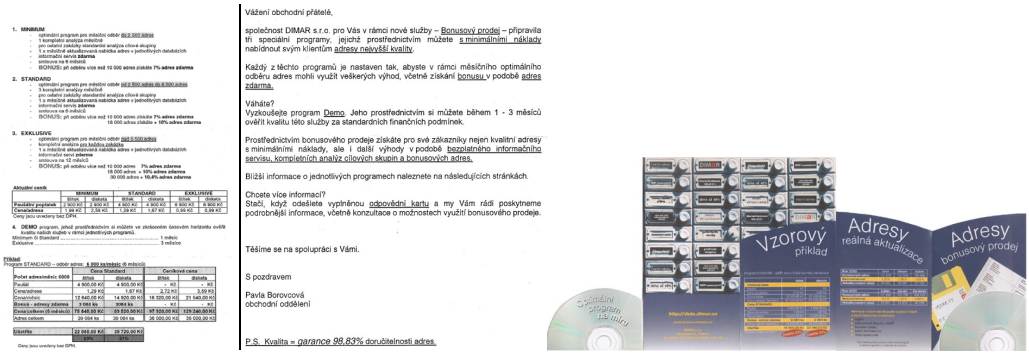
Time	Processes	Critical for
2 s	**Attention**, aperception	Journal ads, logos
5 s	**Orientation**, particular words, anchoring elements	Billboards, city lights
10 s	**Manipulations**, shallow reading, short time memory, mental representations	Parts of mailings, TV spots
~ 60 s	**Searching strategies**, deep reading, antimanipulative behavior, satiety time constants, etc.	Whole mailings, web pages

Table – Time span and important processes, which are critical for successful communication

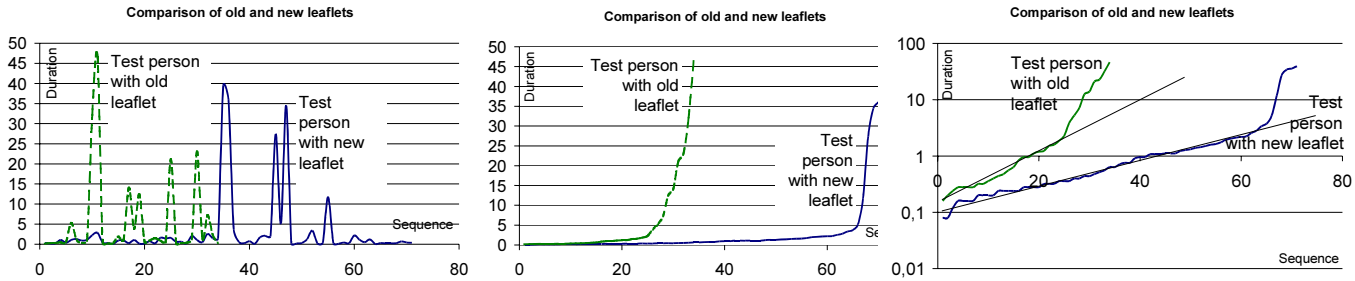
The simplest way how to separate particular contributing factors is simple sorting of gazes from shortest one to longest one. This way we have short time processes (like saccades – fixations) at the left side of the chart, and longer time processes (like time satiety constant) at the right side.

Despite a fact that duration of particular eye fixation use to be fairly constant, the distribution of gazes, i.e. collections of fixations and saccades, has no clear central tendency. The curve of growing gaze duration is monotonic, but it was surprising that we encountered in many observations that there is a tendency to build up a line progressions in logarithmic scale, at least in some part of the sorted chart (see presentation). There is no plain explanation for this repeating phenomenon.

By comparison of various types of visual materials, it seems to be probable, that the more visually attractive the material is, the smaller slope the line progression has. See following picture for an illustration.



Picture – Old black and white cheap layout and new colorful expensive layout



Picture – Striking differences between persons who look at old and new mailing

All charts have a plotted sequence of gazes on x axis, and duration on y axis on the first chart. We see a long row of short gazes in the case of the second person in original sequence. The both men had the same total time spent on the reading of the mailings despite the fact the two plots look very differently. The second chart shows the same information, only the gazes are sorted according to duration for every man. The third chart is the second one with logarithmic scale on the y axis. We see clearly that the gazes are pretty linear up to time 1.2 seconds. There is some breaking time after this duration, and the line either changes the shape of only slope. We can encounter such linear progression in many researches, which suggest some regularity.

The regularities suggest following hypothesis:

1) Although the time of a single eye fixation is fairly constant with normal distribution, on other side, the gaze duration distribution on some visual has rather exponential or Poisson distribution.
2) A bigger predictive value has seemingly a logarithm of gaze duration rather than duration as such.
3) Breaking duration is probably a milestone of change in the way of processing of the material. The information flow probably changes its characteristics before and after breaking duration. Therefore the gazes before and after the breaking duration should be evaluated separately and differently.
4) Short gaze duration (cca <1.2s in this case) seems to be related to visual attractiveness or complexity of the material. Longer gaze duration seems to reflect rather systematic gathering of information.
5) Total number of gazes is theoretically independent from slope of the line in logarithmic slope.

But to test these hypotheses, we have to have some basic description of the gaze distribution, which allow us to describe the eye behavior on a given material with minimum parameters. This article is devoted to search for some suitable parameters, which can describe regularities mentioned above.

1.1 Fitting model

Every pictorial representation of data is somehow biased. The sorted charts are amplifying differences in long gazes. When we take the same data and make a frequency histogram, it will be amplifying short gazes. As

we want to describe first of all these short gazes, it would be more useful to try to find a fitting function of frequency histogram, which more common and more convenient for statisticians anyway. But we have to keep in mind that it underestimates the importance of long gazes, which are more important for marketing point of view.

As a fitting function, we used exponential distribution, which has just one (!) parameter, which corresponds to the slope of sorted gazes and fitted by least squares method. For every frequency vector we find minimal residuum R^2, using Excel's solver.

$$E_i = \frac{e^{-\lambda * d_i}}{\sum_i e^{-\lambda * d_i}} \qquad O_i = \frac{n_{d_i}}{\sum_i n_{d_i}} \qquad R^2 = \sum_i \left(E_i - O_i\right)^2$$

Picture – Equations used to fit frequency tables

E means expected value, *O* observed value, *R* residuum, *i* is number of coding steps, frames, *e* Euler number, *n* frequency (count of gazes) with a particular duration *d*.

2. Study 1 - gazes on product fields of a grocery catalogue

2.1 Methodology and data acquisition

We took simpler example for this case and namely two middle pages of grocery catalogue of Czech Penny market with evenly spaced product in 6*4 grid and only one headline (46) of an area of 3 fields of the grid. We will call these fields codes with respective number according following table:

1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	16
17	18	19	20
21	22	23	24

25	46		
26	27	28	29
30	31	32	33
34	35	36	37
38	39	40	41
42	43	44	45

Picture – Tested material and map of codes

Seven female consumers were presented bulk of advertisement materials with an instruction: “Go through it, as if you were at home.” Their eye behavior was recorded by head mounted eye tracker ASL 4000 and digitized to MPG files (25 frames per second; 1 frame = 1 coding step).

Eye behavior was carefully coded by keeping following rules in dubious cases (edges, lines between products):

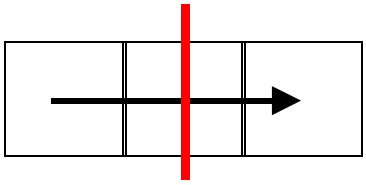
1) Keep current code until it is clear that cursor has moved to another code, area.

2) With saccades to dubious place, decide according subsequent movement.

We get 848 codes including nondef (59) and fault (47) codes. We excluded all gazes (72) from consequent analysis, those duration might be effected by neighboring fault, i.e. missing signal of eye-tracker. There remain 670 codes that were analyzed.

Count 670 Sum 5731 Mean 8.55 SD 10.51 (in steps 0,04s)

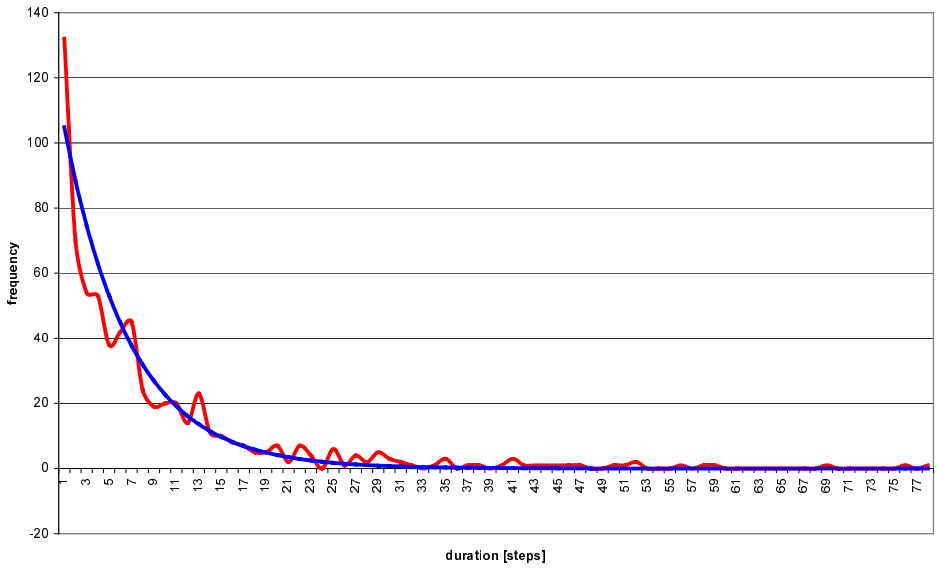
We are aware that coding procedure biases the shortest gaze duration that way, that is can include also gazes that were shorter then one step. Coding procedure can capture passing gazes that at the particular coding were shorter time than 0,02 s, but the signal of eye-tracker reports gaze at the particular code.

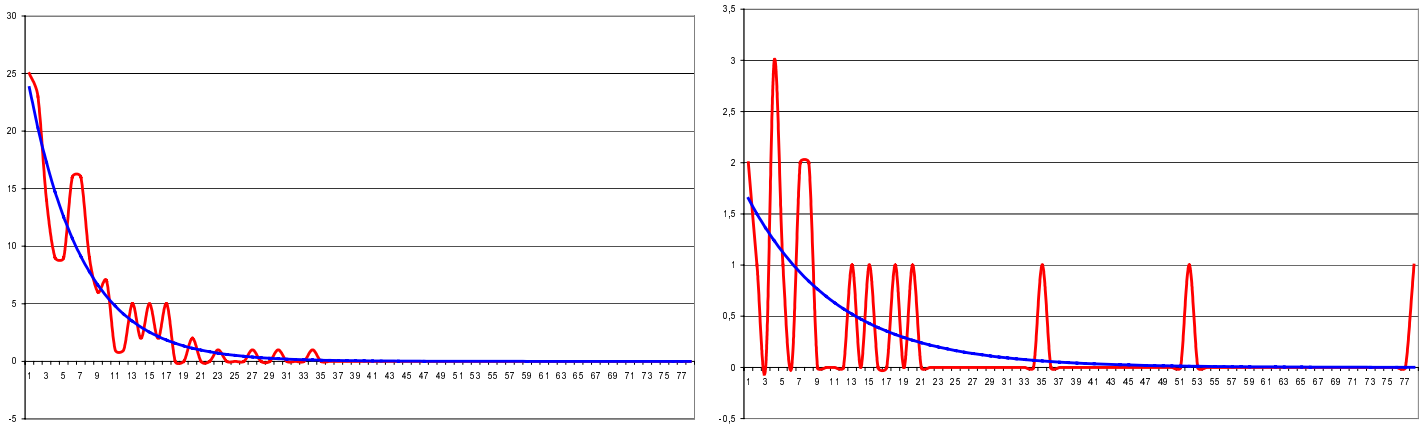


An arrow is a short saccade (<0,02s) over pictures of three products, unfortunately the coding procedure captured the gaze in the moment when it was flying over the middle, least important square. This way is number of shortest gazes overestimated. But we did not exclude these numbers from analysis, as it is a well-defined bias at the very beginning of fitting curves.

2.2 Data fitting

We can fit all acquired data, a particular test person or a particular product with described fitting function.





Picture – Frequency charts with fitting curves

All three charts have duration of a gaze on x-axis and number of gazes on y-axis. There are all data on the first chart, seventh test person on the second and first product on the third chart. We see that for all test-person is fitting quite well, as there are not missing gaps in duration. The decreasing probability is depicted as growing gaps between teeth in the sparse chart of the product. We should have on mind that we are trying to fit discrete numbers with continuous curve.

	R2	Lambda
All data	0,0050	0,170
7th test person	0,0076	0,160
1st product	0,0493	0,096

Test person	R2	Lambda
1	0.021	0.21
2	0.035	0.17
3	0.011	0.18
4	0.009	0.19
5	0.041	0.18
6	0.015	0.13
7	0.007	0.16

P	λ	P	λ	P	λ	P	λ	P	λ	P	λ	P	λ
1	0.1	8	0.28	15	0.53	22	0.13	29	0.09	36	0.21	43	0.08
2	0.14	9	0.14	16	0.25	23	0.09	30	0.27	37	0.41	44	0.16
3	0.22	10	0.19	17	0.1	24	0.12	31	0.19	38	0.1	45	0.05
4	0.21	11	0.24	18	0.18	25	0.07	32	0.18	39	0.23	46	0.27
5	0.26	12	0.17	19	0.08	26	0.24	33	0.14	40	0.18		
6	0.25	13	0.16	20	0.23	27	0.25	34	0.18	41	0.12		
7	0.14	14	0.11	21	0.33	28	0.08	35	0.18	42	0.07		

3. Study 2 - difference between left and right pages

3.1 Methodology and data acquisition

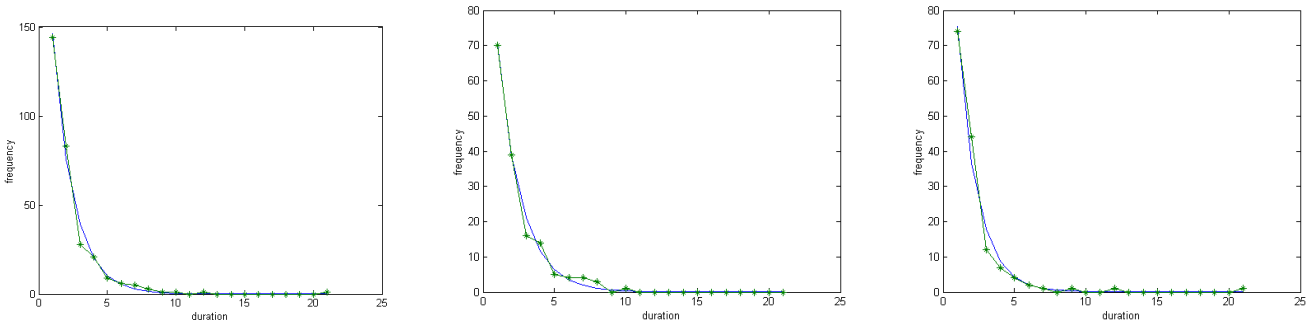
We took much codes with much bigger area than were a product field in previous example, namely whole pages in Czech grocery store Hypermarket. We changed also a coding step, from 0,04 to 0,2 seconds. There were only three test persons, again customers of the store. The catalogue pages looks similar to previous catalogue Penny Market, there was no remarkable difference in layout at right and left pages. We coded them to acquire the difference in gaze distribution between left and right middle pages.

Left page is supposed to have less people's attention (cheaper for advertizing)	Right page considered to be better for advertising in marketing (higher prices)

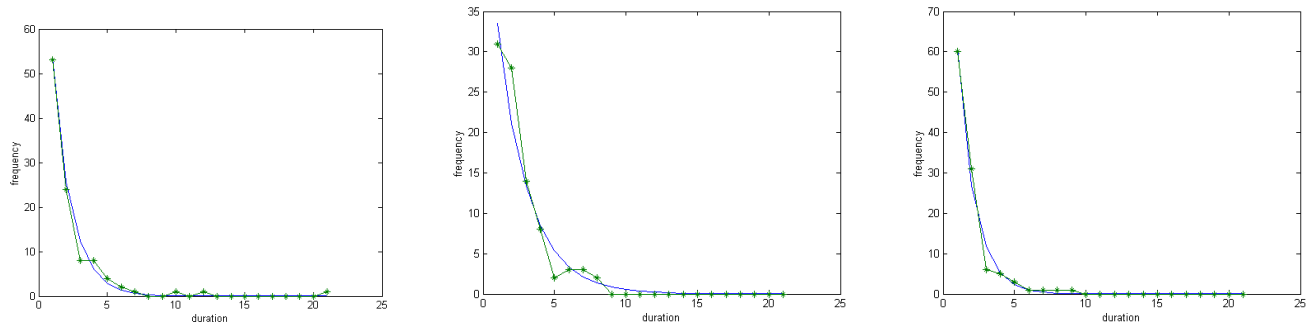
Person	Left page	Right page	Sum	Person	Left page	Right page	Count	Person	Left page	Right page	Average
1	26,2	21,6	**47,8**	1	56	47	**103**	**1**	0,47	0,46	**0,46**
2	26,4	18,8	**45,2**	2	49	42	**91**	**2**	0,54	0,45	**0,50**
3	20	21	**41**	3	51	58	**109**	**3**	0,39	0,36	**0,38**
Sum	**72,6**	**61,4**	**134**	**Count**	**156**	**147**	**303**	**Average**	**0,47**	**0,42**	**0,44**

3.2 Data fitting

We fit the data using the same methodology as before.



All data fit, Left page, Right page



Test persons: 1, 2, 3

	R^2	Lambda
All data	0.0021	0.66
Right page	0.0044	0.72
Left page	0.0018	0.60
TP1	0.0029	0.73
TP2	0.0081	0.46
TP3	0.0046	0.82

Average Lambda either of pages or test persons is equal to lambda of all data.

4. Modeling data

We can also take a fitting curve as model of gaze duration distribution for various lambdas.

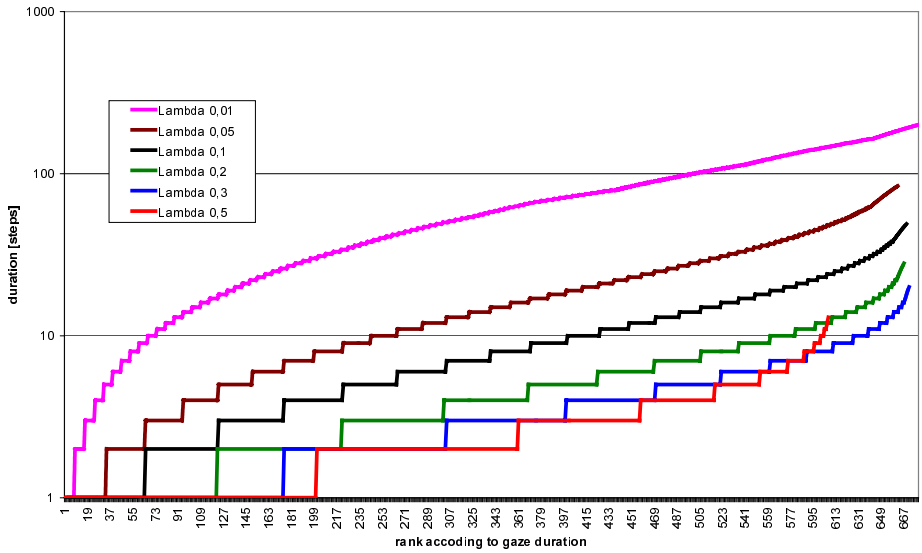
duration [steps]	$q=e^{(-\lambda*d)}$	$p=q/\Sigma q$	$n_d=p.N$	rounded n_d
1	0,843	0,156	104,819	105
2	0,711	0,131	88,420	88
3	0,600	0,111	74,587	75

4	0,506	0,093	62,918	63
...				

λ= 0,1701 Σq= 5,391 Σp=1 N=670

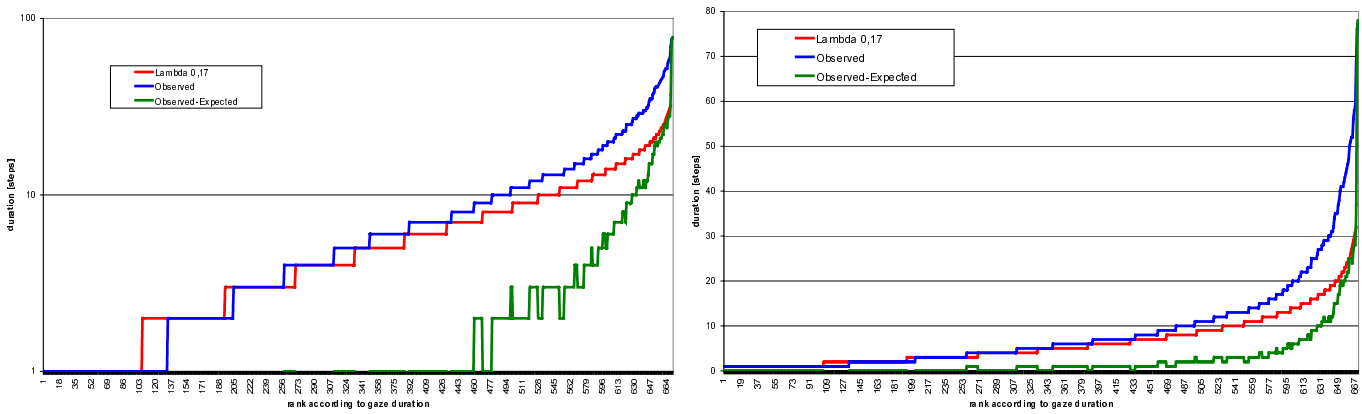
Picture – Table modeling frequencies of gazes for particular lambda and number of gazes

The table shows how modeled data were generated according to rounded n_d and particular duration.



Picture – Rank chart for different lambda

All three charts have duration of a gaze on x-axis and number of gazes on y-axis. There are all data on the first chart, seventh test person on the second and first product on the third chart. We see that for all test-person is fitting quite well, as there are not missing gaps in duration. The decreasing probability is depicted as growing gaps between teeth in the sparse chart of the product. We should have on mind that we are trying to fit discrete numbers with continuous curve.



Picture – Rank charts comparing modeled and observed data

The logarithmic and normal axis views show that disparity between modeled and observed data is mostly in long gazes, which was expected.

We get a disparity in long duration by comparing modeled data with observed ones. Area of the different can be reasonably ascribed to reading processes, which got involved in longer duration. Sum of this reading time is 1550 steps, i.e. 8,9s per person. So we can assume that a test person spent 4,5 second per page by reading and higher level processes.

5. Discussion

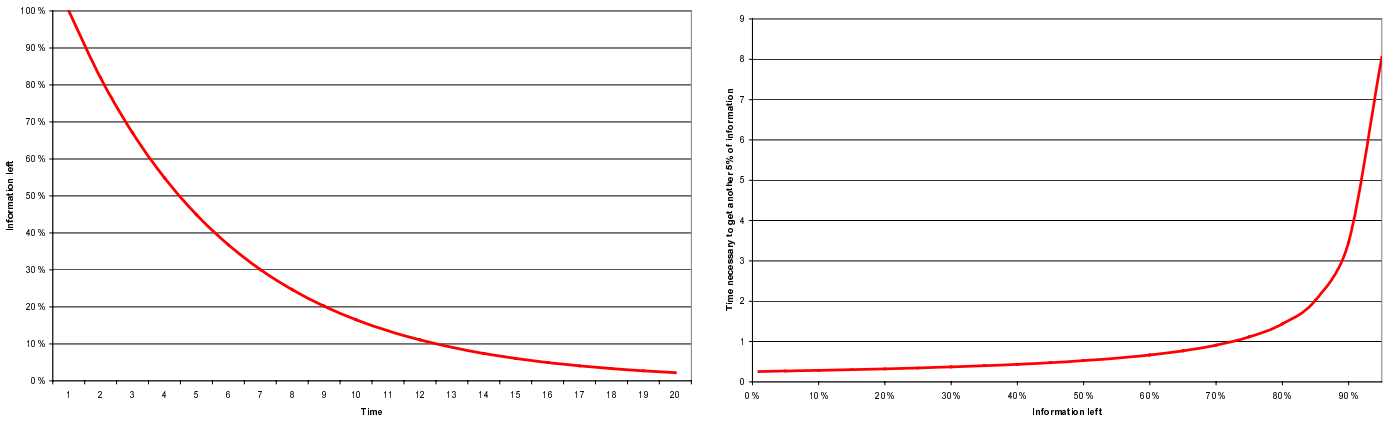
5.1 A visual target like a collector of information

We talked mostly about how to fit measured data up to now. Let's turn our attention to a consideration, why the data have such distribution. Human visual system has evolved to maximize it efficiency in gathering information despite the very limited capacity and resources it posses.

We know that there is a low lever timing process, which generates an impulse for a saccade three times per second in average. It can be temporarily suppressed by will but not for long time. This process can have an analogy in a bouncing ball. A brain collects a chunk of an information every jump. These physiological fixations have more or less normal distribution. Let's go on with our analogy with a ball. A basketball player is not free whether he can dribble a ball or not, he had to follow given rules, but he is allowed to decide whether he will dribble on his left or right side. The similar way, a brain can freely decide how much it will dribble fixations on a particular target, and we saw it takes place in some exponential way. What optimal, resources sparing strategy is behind?

Let's think about a target as a collector of information with limited capacity. This capacity is possibly not emptied in linear way. We can easy collect some elementary information just by a single fixation (color, possible orientation of a paper) but it takes much more time to process the rest of information and the time must be prolonged to get equivalent amount of information. Let's take a model a discharging a capacitor from electronics and apply it on our visual target. Voltage is equivalent to information load.

$$Information\ left = e^{\lambda \times time}$$



Picture – Rank charts comparing modeled and observed data

If the visual target is like a capacitor, than a human brain cannot extract information in linear way. There are still some possible other information but it is more and more time consuming to get it. The chart on the right shows how time increase that is necessary to get another 5 % of information with lambda=0,2. We can see that around 5 time steps are sufficient to get 50 % of information with given lambda.

If a brain wants to sustain constant information flow from particular gaze at a target, it must prolong duration of gaze in a logarithmic way. This prediction is in accordance with observed data.

5.2 Ideal observer and multiple targets

If a test person were presented multiple target material, it would be not an optimal strategy to stay on a one target for longer time. On contrary, it is more advantageous to run in a quite fast tempo through many targets, as he can get 20 % of information from every target just during an only one visit. Collected information

is concurrently evaluated during these first brief visits. An evaluation could be a factor weighting remaining information on the particular target. It is important to realize, that lambda is a constant that describes, how easy the given material releases information, i.e. the higher lambda the easier the material is to read. Weighting of material is person's evaluation of already collected information.

Let's have two targets with different readability lambda (0,4 versus 0,1) and different final evaluation factor (10% versus 90%) and we can see how these two factors compensate each other:

Time needed to collect information	Duration of next gaze	Information left (IL)	Weight of information	Estimated profit
=-ln(1-information left)/lambda	time difference	constant information flow of 5% by each step	decreasing function evaluating extracted information	=information left * weight

step	Information left	Time 1	Duration 1	Weight 1	Profit 1	Time 2	Duration 2	Weight 2	Profit 2
0	1,00	0,00	0,10	100%	1,00	0,00	0,51	100%	1,00
1	0,95	0,10	0,11	95%	0,91	0,51	0,54	100%	0,95
2	0,90	0,21	0,11	91%	0,82	1,05	0,57	99%	0,89
3	0,85	0,33	0,12	86%	0,73	1,63	0,61	99%	0,84
4	0,80	0,45	0,13	82%	0,65	2,23	0,65	98%	0,78
5	0,75	0,58	0,14	77%	0,58	2,88	0,69	98%	0,73
6	0,70	0,71	0,15	73%	0,51	3,57	0,74	97%	0,68
7	0,65	0,86	0,16	68%	0,44	4,31	0,80	97%	0,63
8	0,60	1,02	0,17	64%	0,38	5,11	0,87	96%	0,58
9	0,55	1,20	0,19	59%	0,32	5,98	0,95	96%	0,53
10	0,50	1,39	0,21	55%	0,27	6,93	1,05	95%	0,48
11	0,45	1,60	0,24	50%	0,22	7,99	1,18	95%	0,43
12	0,40	1,83	0,27	45%	0,18	9,16	1,34	94%	0,38
13	0,35	2,10	0,31	41%	0,14	10,50	1,54	94%	0,33
14	0,30	2,41	0,36	36%	0,11	12,04	1,82	93%	0,28
15	0,25	2,77	0,45	32%	0,08	13,86	2,23	93%	0,23
16	0,20	3,22	0,58	27%	0,05	16,09	2,88	92%	0,18
17	0,15	3,79	0,81	23%	0,03	18,97	4,05	92%	0,14
18	0,10	4,61	1,39	18%	0,02	23,03	6,93	91%	0,09
19	0,05	5,99	3,22	14%	0,01	29,96	16,09	91%	0,05
20	0,01	9,21	7,82	10%	0,00	46,05	39,12	90%	0,01

Picture – Competition of two targets different in readability and attractiveness

The target one is easy to read (readability lambda=0,4) but is not interesting to the test person (final evaluation is 10 %). The second target has poor lambda=0,1, but is very interesting (90 %). These two factors can compensate each other, so when the person is following lessening expected profit, it creates common cyclic pattern of eye movements between two targets, what we will see bellow.

If the visual target is like a capacitor, than a human brain cannot extract information in linear way. There are still some possible other information but it is more and more time consuming to get it. The chart on the right shows how time increase that is necessary to get another 5 % of information with lambda=0,2. We can see that around 5 time steps are sufficient to get 50 % of information with given lambda.

			Target 1		Profit	Target 2	
step	Time	Target	Duration	IL		Duration	IL
0	0,1	1	0,1	1	1		
1	0,61	2			1	0,51	1
2	1,15	2			0,95	0,54	0,95

3	1,26	1	0,11	0,95	0,91		
4	1,83	2			0,89	0,57	0,9
5	2,44	2			0,84	0,61	0,85
6	2,55	1	0,11	0,9	0,82		
7	3,2	2			0,78	0,65	0,8
8	3,32	1	0,12	0,85	0,73		
9	4,01	2			0,73	0,69	0,75
10	4,75	2			0,68	0,74	0,7
11	4,88	1	0,13	0,8	0,65		
12	5,68	2			0,63	0,8	0,65
13	5,82	1	0,14	0,75	0,58		
14	6,69	2			0,58	0,87	0,6
15	7,64	2			0,53	0,95	0,55
16	7,79	1	0,15	0,7	0,51		
17	8,84	2			0,48	1,05	0,5
18	9	1	0,16	0,65	0,44		
19	10,18	2			0,43	1,18	0,45
20	10,35	1	0,17	0,6	0,38		
		Total	**1,19**	**0,6**		**9,16**	**0,45**

Picture – Competition of two targets different in readability and attractiveness

The target one is easy to read (readability lambda=0,4) but is not interesting to the test person (final evaluation is 10 %). The second target has poor lambda=0,1, but is very interesting (90 %). These two factors can compensate each other, so when the person is following lessening expected profit, it creates common cyclic pattern of eye movements between two targets, what we will see bellow.

When we put together the two target and sort them by expected profit, we get cyclic structure, which is quite similar to what we saw by eye-tracking data. In this setting it proves that high weighting overrides bad readability of the second target.

5.3 Conclusion

We can find in literature some incorporation of distribution of gazes based on general gamma distribution (Rik Pieters, Chris Janiszewski, etc.) But their regression models are quite particular and we cannot use them in general daily praxis of eye-tracking research of commercial materials.

Presented model shows easy way how to estimate one statistical parameter which characterize any set of gazes and is independent from the number of gazes. This is a practical tool for evaluation and comparison of different stages and materials among themselves.

6. References

Chandon J. Pierre, Hutchinson Wesley: Unseen is Unsold: Assessing Visual Equity with Commercial Eye-Tracking Data

Fox, Richard J., Dean M. Krugman, James E. Fletcher, and Paul M. Fischer (1998), “Adolescents' Attention to Beer and Cigarette Print Ads and Associated Product Warnings,” Journal of Advertising, 27 (3), 57-68.

Hutchinson, J. Wesley, Kalyan Raman, and Murali K. Mantrala (1994), “Finding Choice Alternatives in Memory: Probability Model of Brand Name Recall,” Journal of Marketing Research, 31 (November), 441-461.

Janiszewski, Chris (1990), “The Influence of Print Advertisement Organization on Affect toward a Brand Name.,” Journal of Consumer Research, 17 (Jun., 1990), 53-65. janiszewski4.pdf

Janiszewski, Chris (1998), “The Influence of Display Characteristics on Visual Exploratory Search Behavior,” Journal of Consumer Research, 25 (December), 290-301. janiszewski1.pdf

Lohse, Gerald L. (1997), “Consumer Eye Movement Patterns on Yellow Pages Advertising,” Journal of Advertising, 26 (1), 61-73.

Lohse, Gerald L. and Eric J. Johnson (1996), “A Comparison of Two Process Tracing Methods for Choice Tasks,” Organizational Behavior and Human Decision Processes, 68 (1), 28-43.

Rayner, Keith (1998), “Eye Movement in Reading and Information Processing: 20 years of Research,” Psychological Bulletin, 124 (3), 372-422.

Rosbergen Edward, Pieters Rik, Wedel Miechel: Visual attention to advertising: A segment-level analysis. The Journal of Consumer Research, Volume 24, Issue 3 (Dec., 1997), 305-314

Rosbergen, Edward, Rik Pieters, and Michel Wedel (1997), “Visual Attention to Advertising: A Segment-level Analysis,” Journal of Consumer Research, 24 (3), 305-314.

Russo, J. Edwards (1978), “Eye Fixations can Save the World: A Critical Evaluation and a Comparison Between Eye Fixations and Other Information Processing Methodologies” in Advances in Consumer Research, H. K. Hunt, Eds., Ann Arbor, MI: Association for Consumer Research, 561-570.

Russo, J. Edwards and France Leclerc (1994), “An Eye-Fixation Analysis of Choice Processes for Consumer Nondurables,” Journal of Consumer Research, 21 (September), 274-290.

Russo, J. Edwards and Larry D. Rosen (1975), “An Eye Fixation Analysis of Multialternative Choice,” Memory and Cognition, 3 (3), 267-276.

Von Keitz, Beate (1988), “Eye Movement Research: Do Consumers Use the Information They Are Offered?,” Marketing and Research Today, 16 (4), 217-224.

Wedel, Michel and Rik Pieters (2000), “Eye Fixations on Advertisements and Memory for Brands: A Model and Findings,” Marketing Science, 19 (4), 297-312.