

# Information Sciences and Technologies Bulletin of the ACM Slovakia



Association for  
Computing Machinery

*Advancing Computing as a Science & Profession*

December 2019  
Volume 11, Number 2

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Typeset in L<sup>A</sup>T<sub>E</sub>X using style based on ACM SIG Proceedings Template.

# Modelling of Human Visual Attention

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## Abstract

In recent decades, visual attention modelling became a prominent research area. In order to simulate human attention, a computational model has to incorporate various stimulus-driven and goal-directed attention mechanisms. This work explores how low- and mid-level features such as color, motion, depth and shape influence visual attention in our own eye-tracking experiments. To measure these effects, we utilized various state-of-the-art as well as novel computational models which estimate saliency of a specific feature. In order to deeper understand the process of selective attention in everyday actions, we conducted several experiments in real environments recorded from the first-person perspective. Our results showed that egocentric attention is very individual and differs from 2D image viewing conditions, partially due to binocular cues that enhance viewer's perception. We therefore suggest to employ specialized models for egocentric vision. Finally, we found out that high-level factors such as individual's emotions and task-based analysis of visualizations influence human gaze behavior too.

## Categories and Subject Descriptors

I.2.10 [Artificial Intelligence]: Vision and Scene Understanding—*Perceptual reasoning*; I.4.8 [Image Processing and Computer Vision]: Scene Analysis—*Color, Depth cues, Motion, Shape*

## Keywords

visual attention, saliency model, egocentric attention

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\*Recommended by thesis supervisor: Assoc. Prof. Vanda Benešová  
Defended at Faculty of Informatics and Information Technologies, Slovak University of Technology in Bratislava on July 8, 2019.

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Polatsek, P. Modelling of Human Visual Attention. Information Sciences and Technologies Bulletin of the ACM Slovakia, Vol. 11, No. 2 (2019) 1-9

## 1. Introduction

*Visual attention* is a set of cognitive processes that selects relevant information and filters out irrelevant information from the environment [4]. Therefore, it plays an important role in the control of head and eye movements. Scene scan is performed by a sequence of rapid movements called *saccades* and *fixations*. During a fixation, the eye is relatively still to acquire visual information from the focus of interest [32, 17].

Attention is influenced by both *bottom-up* factors such as salient stimuli and *top-down* factors including individual's goals and prior knowledge. Psychologists assume that bottom-up and top-down processes work together to organize and interpret visual information from the environment. This is referred to as *perception* [8].

Visual saliency has been researched in many research areas including psychology, neurobiology, image processing and computer vision [5]. In general, there are two different approaches how to define saliency of an image [29]. We can *measure saliency*, e.g. using eye-trackers or we can *predict saliency* by computational saliency models. They compute a *saliency map* from an image, representing a topographical map of conspicuousness [5].

The primary goal of this work is to individually study various aspects of visual attention using novel eye-tracking experiments and computational saliency models. Since the majority of these factors has been explored marginally so far, we recorded fixation data in image viewing conditions and real environments to deeper understand human visual system and increase the performance of saliency models.

## 2. Related Work

Recent decades of visual attention research have brought many computational models that can be grouped by various criteria, including [5, 26]:

- **factors influencing attention:** *bottom-up* factors and *top-down* factors,
- **temporality:** *spatial* models based solely on a current scene and *temporal* models based on the accumulated prior knowledge or motion analysis,
- **stimuli type:** *static* stimuli such as intensity, color and depth and *dynamic* stimuli such as motion and flicker,

- **task type:** *free viewing, visual search tasks* and other more *complex tasks* (e.g. driving),
- **saliency units:** *location-based* models that assign saliency values to each location defined by pixels and macro-blocks and *object-based* models that either extract salient objects from location-based saliency or directly compute saliency at object level,
- **size of information** used in saliency estimation: *local* information based only on a subregion of an image, *global* information based on a whole image.

### 3. Egocentric Motion Saliency Modelling

Since egocentric saliency has not been widely explored so far, we evaluated our own spatiotemporal superpixel-based saliency model on a natural shopping task recorded by eye-tracking glasses.

Our model uses a superpixel segmentation [1] to at least partially implement object-based attention. Each superpixel is described by static (intensity, color and orientation) and dynamic (motion) features in multiple scales. Since human gaze is also directed to unexpected, surprising stimuli, saliency estimation includes motion surprise too.

Each video frame is decomposed into intensity, red, green, blue and yellow colors and orientation of gradients by applying Sobel filter. Motion between consecutive frames is calculated by an optical flow algorithm [10]. The distribution of each feature within a superpixel is represented by a histogram.

To follow the multi-scale approach of Itti et al. [22], we generate a Gaussian pyramid, but we employ superpixels instead of pixels. We compare histograms on finer and coarser pyramid scales to compute spatial and temporal saliency. To estimate motion surprise, we compare prior knowledge about motion field with the actual frame at a given location.

The performance of our model has been compared with the spatial location-based model by Itti et al. [22] and the spatiotemporal superpixel-based model by Liu et al. [28] (see examples in Figure 1) using AUC<sup>1</sup> and NSS<sup>2</sup> scores. The evaluation dataset contains gaze data of two participants at a shopping mall who were asked to find specific products.

We found out that static saliency predominates over motion saliency despite of multiple moving objects in subjects' views. Varying performance of computational models (Table 1) indicates that both types of saliency do not affect their attention equally and thereby it could be also guided by depth information and top-down features, e.g. object detection and detection of biological motion.

<sup>1</sup>A saliency map is treated as a binary classifier. Saliency at fixations and some non-fixated pixels are extracted. Fixations with saliency above a gradually increasing threshold and non-fixations above the threshold are considered as TPs and FPs, respectively. The ROC is plotted and the area under the curve (AUC) is computed [9].

<sup>2</sup>The Normalized Scanpath Saliency (NSS) score equals to the average saliency at fixation locations in a saliency map normalized to have a zero mean and a unit standard deviation [9].



Figure 1: Saliency maps estimated by our model (top right), Itti et al. [22] (bottom left) and Liu et al. [28] (bottom right). Fixation is labelled with a red circle.

Table 1: Individual AUC/NSS Scores

Subject	Our	[22]	[28]
#1	.661/0.59	.595/0.35	.649/0.59
#2	.749/0.87	.756/0.91	.742/0.94

In addition to these factors, egocentric saliency modelling should incorporate the effect of surprise from static as well as dynamic stimuli.

### 4. Visual Attention to Color

Color is the fundamental component of visual attention. Saliency is usually associated with color contrasts. Beside this bottom-up perspective, some recent works indicate that psychological aspects should be considered too [14]. However, relatively little research has been done on potential impacts of color psychology on attention. To our best knowledge, a publicly available fixation dataset specialized on color feature does not exist. We therefore conducted a novel eye-tracking experiment with color stimuli and made it publicly available. We studied whether color differences can reliably model color saliency or particular colors are preferably fixated.

In our experiment we showed simple colored objects on a uniform background to 15 participants. We used colors such as red, green, blue, yellow, cyan, magenta, pink and orange (Figure 2).

Fixation data showed a strong correlation with color contrasts in the LAB color space across displayed images. However, individual correlations across participants revealed that attention of some participants was influenced by color contrasts only negligibly (Figure 3). Furthermore, we found only slightly higher fixations of red and yellow colors associated to danger and warning. On the other hand, cyan objects were largely ignored with a remarkable gap in fixations (Figure 4).

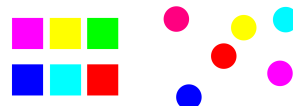
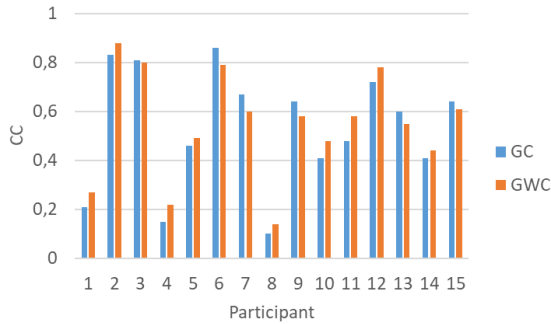
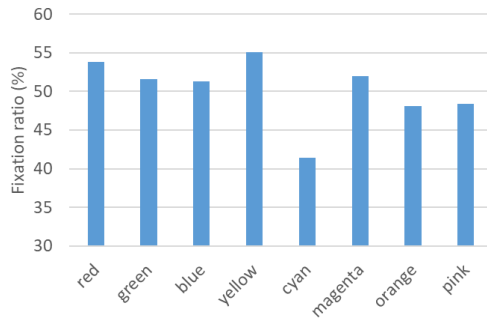


Figure 2: Stimuli in the color experiment.



**Figure 3: Individual average correlations between fixations and color contrasts (GC) and spatially weighted color contrasts (GWC).**



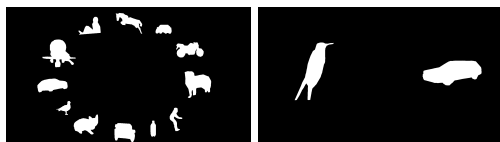
**Figure 4: Fixation ratio of each color.**

## 5. Visual Attention to Shape

Beside simple feature saliency, such as intensity, color and orientation, attention is influenced by object shape and size too. We therefore explored whether and to what extent global and local shape characteristics and their mutual differences affect visual saliency. To our best knowledge, an eye-tracking dataset focused solely on shape has not been available so far. Therefore, we created such a dataset and made it publicly available.

We showed silhouettes of abstract shapes and real-world objects on a uniform background to 73 students in our experiment. Each scene contains either 12 shapes organized in a circle or 2 shapes on both image sides (Figure 5).

To investigate shape saliency, we proposed three groups of computational models. They employ shape descriptors and matchers to detect salient shapes (object-based models) or salient boundary contours (location-based models). The first group of models estimates object saliency by global geometrical properties ignoring the spatial context. Higher saliency values are assigned to larger, asymmetrical, irregular and highly curved objects represented by area size, perimeter length, equivalent diameter, eccentricity, aspect ratio, extent, rectangularity, solidity and circularity. The second group of models assigns higher



**Figure 5: Stimuli in the shape experiment.**

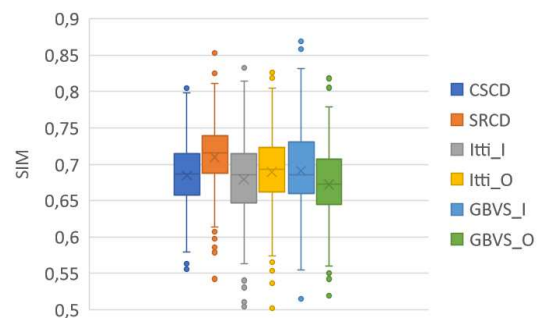
saliency values to shapes that are different from the other ones. The unique shapes are defined by the simple characteristics employed in the first group of models, Hausdorff distance, shape context, centroid distance in the spatial and the frequency domain and boundary moments [37, 3]. In contrast, the third group estimates contour saliency. These models consider contours differ from their surroundings as salient. The first contour model denoted **C-SCD** follows the center-surround approach [22]. It therefore builds a Gaussian pyramid from the centroid distance signature and compares finer and coarser pyramid levels. The second contour model denoted **SRCD** applies a Fourier transform on the centroid distance. It is based on a work of Hou and Zhang [21] that introduced the spectral residual approach to create a saliency map. Beside own models, we evaluated the shape saliency model based on the Jaccard index [11] and two standard models [22, 18] that compute intensity and color saliency which could participate in shape perception too.

We found out that attention is directed to larger objects (see significant positive correlations in Table 2), but we did not observe a clear trend for fixating asymmetrical and complex objects. The results also showed that saliency from global shape contrast only slightly affects attention. Finally, our analysis revealed a significant effect of contour saliency. Comparing contour models using SIM metric<sup>3</sup> as visualized in Figure 6, our **SRCD** significantly outperforms other location-based models (see example in Figure 7). In addition, human-like figures seem to be often more salient than silhouettes of non-living objects, particularly human and animal heads.

<sup>3</sup>The similarity metric (SIM) is defined as  $\sum_x (S(x), F(x))$ , where saliency  $S$  and continuous fixation map  $F$  are normalized to the sum of 1 [9].

**Table 2: Correlation Between Fixations and Shape Properties such as Area Size (A), Equivalent Diameter (ED) and Perimeter Length (P). All Correlations are Significant ( $p < .001$ )**

Objects	A	ED	P
2	0.39	0.40	0.31
12	0.29	0.30	0.54



**Figure 6: SIM scores of location-based saliency models – centroid distance in the spatial (CSCD) and the frequency domain (SRCD), intensity and orientation saliency by Itti et al. [22] (Itti\_I, Itti\_O) and Harel et al. [18] (GBVS\_I, GBVS\_O).**

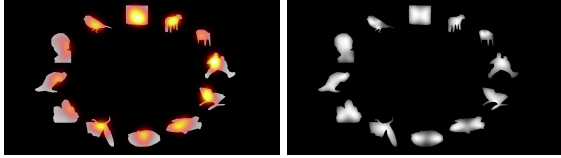


Figure 7: Fixation heatmap and saliency map estimated by SRCF.

## 6. Visual Attention to Egocentric Depth

Computational models usually do not employ depth information to estimate saliency. However, depth is an important aspect of visual attention in egocentric vision. In contrast to previous studies that investigated depth on 2D and 3D images, our experiments whose fixation data are publicly available took place in a natural environment. Since binocular vision enhances depth discrimination [2, 31], we explored in our eye-tracking experiment whether saliency of depth in natural 3D environment differs from pictorial depth.

We recorded fixations of 28 students in a room with identical balls arranged in an octagonal layout whose distance from an observer varied, up to 4 m (6 depth planes with a step of 30 cm). Participants were shown 5 scene types that differ in depth level steps between adjacent objects – the only one step of 1; alternating zero steps and steps of 2; only steps of 1; steps of 1, but one step of 3 and steps varying from 0 up to 4 (Figure 8). We represented each object by the relative depth and the global depth contrast.

We cannot confirm the finding of experiments with 2D and 3D images [23, 25, 35] which concluded that fixations are biased towards areas close to a viewer. Surprisingly, our results indicate that attention is more strongly directed towards distant objects in a real environment, but this relationship between saliency and depth is non-linear (Figure 9). Despite of this bias we believe there is a threshold distance when object saliency starts to decrease since their size is relatively too small to grab attention. Furthermore, high-contrast objects in depth channel are salient even though this effect is also not linear (Figure 10).

Therefore, we conclude that human gaze behavior in real environments differs from stereoscopic image displays and standard 3D saliency models incorporating depth channel are not suitable for egocentric video sequences.



Figure 8: Example scene in the depth experiment.

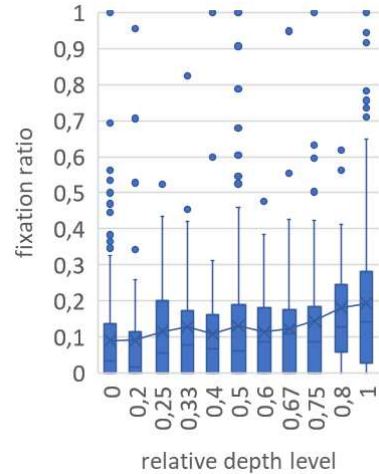


Figure 9: Distribution of participants' fixations on depths, ranging from 0 (closest) to 1 (farthest).

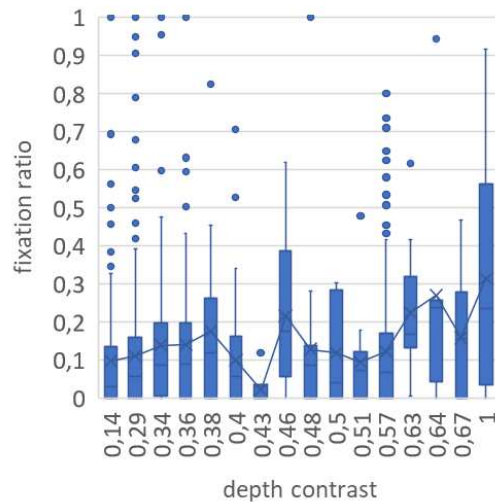


Figure 10: Distribution of participants' fixations on depth contrasts, normalized between 0 and 1.

## 7. Static Feature-Based Egocentric Visual Attention

Our experiments explored the effects of static features on attention separately (Section 4, 5 and 6). The aim of this section is to find out how static stimuli compete for our attention in everyday actions. In contrast to prior works, we analyzed scene depth too.

Our experiments employed eye-tracking glasses to record users' gaze and Kinect device to capture depth of objects. 6 students were asked to freely walk and explore a laboratory room which contains only static stimuli for 15 up to 30 sec.

We analyzed low-level features such as intensity, color, orientation and depth, mid-level features such as object shape and contours and the center bias. We predicted their saliency effects by conventional [22, 18] and novel computational models that decompose overall attention to separate feature saliency maps:

1. Intensity (I), color (C) and orientation (O):
  - (a) Itti et al's model [22] (denoted **Itti** with suffixes **\_I**, **\_C** and **\_O**, respectively),
  - (b) Harel et al's model [18] (denoted **GBVS** with suffixes **\_I**, **\_C** and **\_O**, respectively),
  - (c) own superpixel model which correlates superpixel histograms at finer and coarser pyramid layers for intensity and orientation saliency (the highest saliency is estimated for uncorrelated superpixels) and compares their color distances for color saliency (denoted **SPX** with suffixes **\_I**, **\_C** and **\_O**, respectively; Section 3).
2. Depth (D):
  - (a) simple model which linearly increases saliency with shorter object distance to a viewer so that the closest objects are most salient (denoted **D\_lin**),
  - (b) experimental model based on our depth experiment (denoted **D\_nlin**; Section 6),
  - (c) simple contrast model which defines saliency linearly as global contrast of superpixels<sup>4</sup> (denoted **DC\_lin**),
  - (d) experimental contrast model which weights the contrast of superpixels<sup>4</sup> based on our depth experiment (denoted **DC\_nlin**; Section 6),
  - (e) our superpixel model which correlates superpixel histograms of depth as in **SPX\_I** (denoted **SPX\_D**; Section 3).
3. Shape (S):
  - (a) perimeter model that assigns higher saliency to larger regions defined by perimeter length (denoted **S\_p\_intra**; Section 5),
  - (b) perimeter model based on region contrasts<sup>4</sup> (denoted **S\_p\_inter**; Section 5),
  - (c) equivalent diameter model that assigns higher saliency to larger regions defined by equivalent diameter (denoted **S\_e\_intra**; Section 5),
  - (d) equivalent diameter model which measures region contrasts<sup>4</sup> (denoted **S\_e\_inter**; Section 5),
  - (e) CSCD model based on the centroid signature in the spatial domain (denoted **S\_CSCD**; Section 5),
  - (f) SRCD model based on the centroid signature in the frequency domain (denoted **S\_SRCD**; Section 5).
4. Center-bias modelled by Gaussian at the image center (denoted **Center**).

Comparing NSS scores<sup>2</sup> listed in Table 3 revealed the strongest influence of intensity, color and orientation contrasts on egocentric attention. Besides, we observed significantly different gaze behavior among participants. This could be explained by top-down guidance of attention that we ignored in our analysis such as object identification and surprising stimuli over time.

<sup>4</sup>We defined global region contrast as  $S(r_i) = \sum_{i \neq j} D_d(r_i, r_j) \exp(-D_s(r_i, r_j))$ , where  $r_i$  denotes the  $i$ -th region,  $D_d$  is the distance between average region depths and  $D_s$  is the normalized Euclidean distance between region centroids.

**Table 3: Individual NSS Scores (the Highest Value is Bold; the Second and the Third Highest Values are Underlined)**

Model	#1	#2	#3	#4	#5	#6
Itti_I	0.97	1.52	<u>1.79</u>	1.58	1.68	<u>1.77</u>
GBVS_I	0.99	1.65	<u>1.80</u>	1.62	1.61	1.66
SPX_I	<u>1.22</u>	<u>1.85</u>	1.78	<b>1.71</b>	<u>1.82</u>	1.69
Itti_C	0.99	1.11	1.38	1.11	1.69	1.33
GBVS_C	1.09	1.39	1.27	1.48	1.85	1.56
SPX_C	0.73	0.90	1.20	1.48	1.73	1.59
Itti_O	1.11	<u>1.87</u>	1.65	<u>1.66</u>	<u>1.85</u>	<u>1.79</u>
GBVS_O	<u>1.20</u>	<b>2.00</b>	<b>2.02</b>	<u>1.70</u>	<b>2.04</b>	<b>1.95</b>
SPX_O	0.94	1.10	1.27	1.19	1.14	1.51
D_lin	0.14	-0.10	0.29	0.50	-0.23	0.09
D_nlin	0.45	0.66	0.28	-0.03	0.88	0.52
DC_lin	0.49	0.30	-0.19	-0.28	0.64	-0.06
DC_nlin	0.60	0.16	-0.29	-0.33	0.56	-0.10
SPX_D	<b>1.27</b>	1.12	1.17	1.27	1.18	1.23
S_p_intra	0.26	-0.35	-0.51	-0.21	-0.50	-0.44
S_p_inter	0.30	-0.33	-0.48	-0.15	-0.45	-0.41
S_e_intra	0.14	-0.42	-0.58	-0.36	-0.60	-0.54
S_e_inter	0.18	-0.40	-0.55	-0.29	-0.56	-0.51
S_CSCD	0.79	0.91	0.89	0.85	0.99	0.80
S_SRCD	0.86	1.22	1.18	1.06	1.18	1.20
Center	0.98	1.25	0.99	1.08	1.29	1.03

Intensity saliency is best modeled by our **SPX\_I**, whereas color and orientation saliency were predicted with highest accuracy by **GBVS** [18]. On the hand, object distances and global depth contrasts had a much lower effect on egocentric attention. However, depth-weighting approach based on our shape experiment in Section 5 (**D\_nlin**) significantly improved saliency estimation of standard depth weighting (**D\_lin**) for 4 subjects. All these depth models are outperformed by local contrast **SPX\_D** model. Shape saliency was successfully estimated only by contour models – **S\_CSCD** and **S\_SRCD**. Our experiment also confirmed a strong center bias of egocentric gaze behavior.

The results also indicate that the above mentioned effects did not remain constant over time. Simple low-level features seem to affect attention more rapidly, whereas complex features such as shape have a delayed effect.

## 8. Emotionally-Tuned Visual Attention

While psychological studies [36] have confirmed a connection between emotional stimuli and visual attention, there is a lack of evidence, how much influence individual's mood has on visual information processing of emotionally neutral stimuli. In contrast to prior studies, we explored if bottom-up low-level saliency could be affected by positive mood. While recent saliency models aimed to predict attention for affective stimuli [27, 13], conventional saliency models have been never evaluated under a particular emotional state of observers.

Our study examined attention of 10 participants who were randomly induced to experience either a positive mood or a neutral mood by recalling own personal memories. Therefore, they were asked to recall either a happy event or the route they took to an experimental room. After the mood induction, participants were shown natural and synthetic images with valence-neutral stimuli. They were instructed to freely explore the images (**V**), memo-

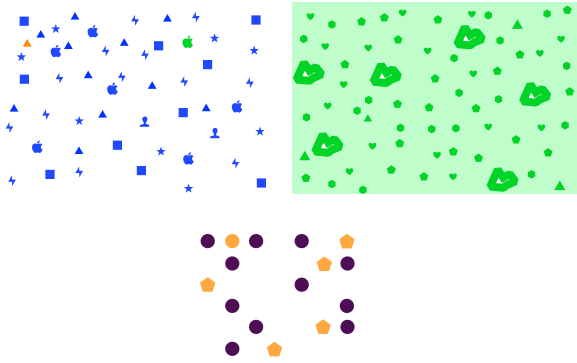


Figure 11: Visual search tasks. FO-task: Find an orange triangle (left). FOA-task: Find a triangle (right). FU-task: Find a unique object (target is the orange circle; bottom).

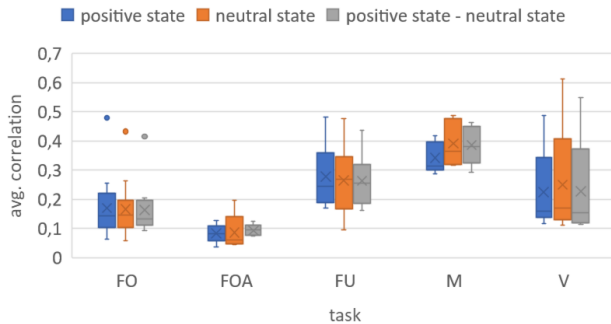


Figure 12: Fixation similarities of subjects with the same emotion and between different emotions.

ribe their contents (**M**) or find a target object as quickly as possible. They searched for a single target among non-targets based on specific criteria (**FO**), any of objects that meets the criteria (**FOA**) or a unique object without explicit target description (**FU**), as shown in Figure 11. Participants assessed their mood in the I-PANAS-SF [24].

Though the mood induction affected only slightly how participants assessed their affective state, we found some differences between both groups of subjects. We assumed that experiences of positive emotions broaden individual’s attention, as proposed by the broaden-and-built theory [15]. However, we found that happy memories could even distract individuals from visual search. While we did not observe significantly similar fixation patterns for participants within as well as between induced emotion (Figure 12), the results suggest the interaction between induced mood and bottom-up saliency [22]. Comparing NSS scores<sup>2</sup>, we found that attention bias towards bottom-up features varies across task type (Figure 13). Positive conditions result in stronger saliency when freely exploring images (**V**). However, the saliency effect is suppressed when solving **FU** and **M**, compared to neutral conditions. We therefore speculate that broadening attention in terms of bottom-up processing might be associated with a low level of engagement in the task.

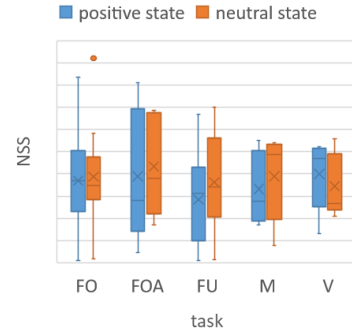


Figure 13: NSS scores of bottom-up saliency model [22].

## 9. Visual Attention during Task-Based Analysis of Information Visualization

The way users observe a visualization is affected by salient stimuli in a scene as well as by domain knowledge, interest, and tasks. While recent saliency models manage to predict users’ visual attention in visualizations during exploratory analysis, there is little evidence how much influence bottom-up saliency has on task-based visual analysis. In contrast to previous studies, we conducted an eye-tracking study whose aim is to determine user’s gaze behavior in visualizations when solving three low-level analytical tasks and made it publicly available.

We analyzed attention of 47 students who were instructed to solve data visualization tasks as quickly as possible. Subjects were shown visualizations from the MASSVIS database such as bar charts, maps, area charts, point charts, tables and line charts that were originally used in the memorability experiment [6]. We designed three low-level analytical tasks for each chart – retrieve value of a specific data element (**RV**), filter data elements based on specific criteria (**F**) and find an extremum attribute value within a dataset (**FE**). To analyze visual performance, we defined task-dependent AOIs that need to be attended to correctly answer the question. We listed their optimal viewing strategy in Table 4 (see examples in Figure 14). We compared participants’ fixations from this confirmatory (task-based) analysis to the memorability experiment (**Mem**) [6] with conditions closer to free exploration.

To estimate bottom-up saliency, we generated saliency maps from 12 saliency algorithms including convolutional neural models and **DVS** model [30] which combines Itti et al.’s saliency [22] with text saliency, and could thereby increase the performance for information visualizations significantly.

Table 4: Optimal Viewing Order of Task-Dependent AOIs

Task	Step 1	Step 2	Step 3
<i>RV</i>	search item label	map to the item	read the value label
<i>F</i>	search value label(s)	map to the item(s)	read the item label(s)
<i>FE</i>	search value label(s)	map to the item(s)	read the item label(s)
	search item(s)		read the item label(s)



Figure 14: Target-dependent AOIs of sub-parts of visualizations. Red, green and blue outlines define the target data points, their item labels and value labels respectively. RV-task: What is the attendance of Universal Studios Hollywood? (left) F-task: Which German states have an unemployment rate of more than 12%? (middle) FE-task: In which country do people anticipate to spend the least money for personal Christmas gifts? (right).

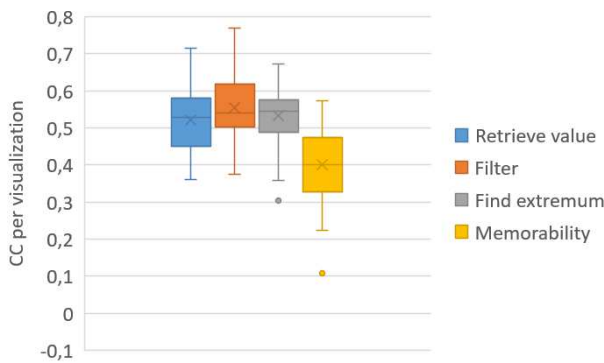


Figure 15: Similarity between fixations of the same type of activity.

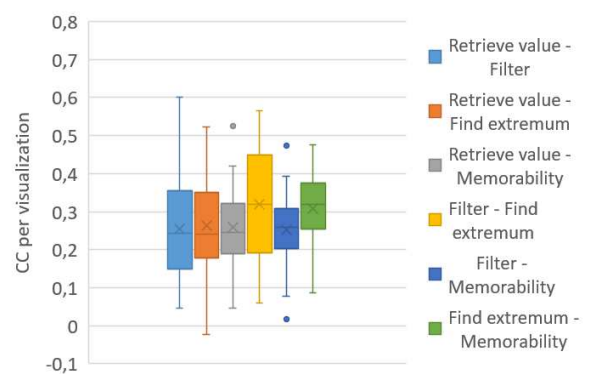


Figure 16: Similarity between fixations of different types of activity.

We found out that fixation patterns of users solving the same analytical task are more coherent than for Mem (Figure 15). However, first fixation times of task-related AOIs revealed that subjects used the optimal viewing strategy in Table 4 only for RV. Analytical tasks therefore seem to have a measurable top-down guidance for the users where to look, but not necessarily in which order. Furthermore, comparing fixations of different types of activity surprisingly showed that Mem much closer resembles FE than other tasks (Figure 16). A possible explanation is that users were intentionally seeking for extrema as representative values to memorize the content of the visualization.

We report the average AUC scores<sup>1</sup> of saliency models in Table 5. In contrast to Itti [22], the performance of DVS [30] confirmed that bottom-up saliency strongly

influences fixations of users when freely exploring the visualization, but has a significantly lower effect on visual attention when performing a low-level analytical task. A potential explanation for this significantly worse performance could be that users direct their attention more towards the data areas than the text areas when performing low-level analytical tasks, than when trying to memorize the visualization. Finally, targets with extreme values in FE are neither more efficiently searched nor more salient in saliency maps [22] than targets of the other two tasks.

To improve existing saliency models and tailor them more towards task-based visual analysis, we therefore recommend to merge classic image-based saliency. The model should localize and identify visualization elements, compare their features and estimate their relationships.

Table 5: The Average AUC Scores for each Task. We Evaluated 12 Saliency Models, Denoted Itti [22] (implementation by Harel [18]), AIM [7], GBVS [18], SUN [39], CAS [16], Sign [20], BMS [38], eDN [34], SAMv and SAMr [12] (Feature Maps Extracted by the Convolutional Neural Model Based on VGG-16 [33] and ResNet-50 [19], Respectively), DVS [30] (with the Optimal Weight of Text Saliency for MASSVIS Database) and TextS [30] (Text Saliency of the DVS Model Separately)

Task	Itti	AIM	GBVS	SUN	CAS	Sign	BMS	eDN	SAMv	SAMr	TextS	DVS
RV	.684	.646	.608	.593	.595	.576	.621	.596	.630	.632	.647	<b>.702</b>
F	.690	.645	.642	.593	.604	.622	.651	.595	.618	.631	.624	<b>.692</b>
FE	.679	.654	.599	.602	.601	.600	.638	.568	.637	.647	.651	<b>.705</b>
Mem	.686	.675	.553	.622	.637	.589	.652	.554	.653	.664	.696	<b>.738</b>

## 10. Conclusions

This thesis explored various bottom-up and top-down factors of visual attention. We performed novel eye-tracking experiments, proposed computational saliency models and discussed human gaze behaviour. Visual attention modelling needs to have specialized fixation datasets which could improve saliency prediction. Therefore, we made our fixation databases available to the public.

Our experiments examined attentional factors separately. Most of them showed a high diversity of their effects on visual attention and visual performance, particularly in natural environments from the first-person perspective which significantly differ from image viewing conditions.

In future work, the above mentioned experimental findings should be merged to create a computational model that could reliably predict attention in natural scenes and specialized domains, such as information visualizations or medical imaging. Because of the individuality in visual information processing, a possible solution could be to learn fixation preference from fixation data of a particular user solving a particular task using deep neural networks.

**Acknowledgements.** This work was supported by the Slovak Scientific Grant Agency, VEGA 1/0874/17, and from the Research and Development Operational Programme for the project “University Science Park of STU Bratislava”, ITMS 26240220084, co-funded by the European Regional Development Fund.

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# Predictive Analytics on Data Streams

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## Abstract

The growing amounts of data brought about the need for transition from offline to online data processing. In our thesis, we explored the utilization of incremental and online data processing in power engineering domain, where this need is imminent because of ongoing introduction of smart metering. We designed two stream processing power demand forecasting methods, which addressed the main requirements of stream mining, i.e., accuracy, timeliness and adaptability. The third requirement relates to changes that occur in stream data over time, i.e., concept drifts. We studied two ways of adaptation of prediction model to the drifts – informed and blind, which differ in incorporation of an explicit change detection mechanism. We proposed incremental forecasting method with informed adaptation and online method with blind adaptation. Both of our approaches equaled the standard batch approaches in accuracy with less computing resources.

## Categories and Subject Descriptors

• **Mathematics of computing** → **Time series analysis**; *Regression analysis*; • **Information systems** → **Data streams**; **Data mining**; **Data stream mining**; *Data analytics*; • **Theory of computation** → **Online learning algorithms**; **Support vector machines**; *Bio-inspired optimization*; • **Computing Methodologies** → **Machine learning**; **Supervised learning by regression**; **Online learning settings**; • **Applied computing** → **Forecasting**.

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\*Recommended by thesis supervisor: Assoc. Prof. Viera Rozinajová  
Defended at Faculty of Informatics and Information Technologies, Slovak University of Technology in Bratislava on December 4, 2019.

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Vrablecová, P. Predictive Analytics on Data Streams. Information Sciences and Technologies Bulletin of the ACM Slovakia, Vol. 11, No. 2 (2019) 10-18

## Keywords

prediction, forecasting, data mining, stream mining, machine learning, incremental, online, adaptive prediction methods, concept drift, power demand forecasting

## 1. Introduction

The data volumes produced by various systems, devices and sensors are continually growing. Likewise, the need for methods, which help humans analyze and discover knowledge from the large volumes of data, is growing. The big data phenomenon is observed since the beginning of this century [12]. Contemporary technologies can already store large data quantities. Since the value of information hidden in data tapers over time, the data must be processed and analyzed online. Therefore, batch processing and analysis are in many cases no longer sufficient and the stream data processing is preferred.

Our thesis is aimed at prediction methods in dynamic environments with continually growing and changing data sets (data streams), which manifest the need for transition from batch to stream processing.

We focused on one application domain – power engineering, because of smart meters' introduction. Smart meters replace the annual physical power consumption meter readings by continual sending of interval measurements (e.g., every 15, 30 or 60 minutes). In the directive no. 2009/72/EC issued by the European Parliament and the Council, all European countries undertook to equip at least 80% of electricity consumers with a smart meter by 2020. Slovakia implemented this obligation in the Act no. 251/2012 on Energy Sector. According to terms in ordinance of Ministry of Economy of the Slovak Republic no. 358/2013, distribution network operators must install the smart meters. By 2020, all the consumers who are connected to the regional or local distribution system with low voltage and their consumption is higher or equal to 4MWh per year should be equipped with a smart meter. That is about 600,000 out of 2.38 million consumers connected to the low voltage [19].

Power suppliers will have at hand large volumes of streaming data for analysis. Analysis of smart metering data is beneficial for all stakeholders of the electricity market. Customers can monitor and lower their own consumption, suppliers can plan the power supply more precisely, invoice the exact amounts of consumed electricity, create tariffs tailored for customers, identify outages and illegal consumption easily, etc. [19].

Since it is hard to store electricity, it is essential to keep balanced voltage of the power grid. Power suppliers are financially penalized for deviations in the grid (i.e., power under/oversupply) the regulatory mechanisms, such as pumped hydroelectric energy storage, must cope with. Therefore, they need to know ahead how much power will their customers (i.e. their balance group) consume. One way to get rid off power under/oversupply is trading at the short-term electricity market. The power can be sold no less than one hour ahead of its consumption. Online analysis of smart metering data can provide very accurate short-term power demand forecasts. For this purpose, automated resources and methods that consider the power consumption properties, are required. The improvement of current power demand forecasts in Slovakia by 1% can lower regulatory fees by millions of euros.

### 1.1 Open Problems

Several research areas overlaps in the selected research challenge. Therefore, we look at the open problems from several perspectives – from the more abstract to the specific ones:

- big data [2]:
  - adjustment of existing and design of new big data analysis methods,
  - easy interpretability of results;
- stream mining [11]:
  - automated and adaptive preprocessing,
  - evaluation of adaptive methods,
  - usability in practice;
- power demand forecasting [8]:
  - usability in practice and easy interpretability of results,
  - mapping and comparison of various existing power demand forecasting methods.

Open problems are based on requirements of individual research areas. Big data requirements are for example scalability, timeliness or human cooperation. In stream data mining, the requirements are mostly related to accuracy, time and memory complexity and adaptability to concept drifts. The advancements of forecasting in power engineering depends on rigorous evaluation, understanding of business needs and learning from many disciplines, such as data mining, statistics, meteorology, etc.

### 1.2 Thesis Goals

The ultimate goal of this thesis was to design a forecasting method that makes short-term forecasts, is adaptive to concept drifts, processes stream data incrementally and forecasts online; and to design a proper evaluation to verify the method's accuracy, ability to adapt to concept drifts and time and memory complexity. We wanted to answer whether incremental and online methods can achieve the accuracy of batch processing, whether incremental method can be still accurate in the presence of concept drifts, how does such method behave during concept drifts, and to what extent can concept drift detection improve the accuracy of forecasting methods.

## 2. Related Work

In the first part of our thesis, we analyzed the theoretical background of research areas that relate to the goal of our thesis – big data, knowledge discovery from data (KDD) and forecasting. We described the big data life cycle, current big data management tools, and we specified in detail the open problems in this area. We captured the KDD process and the basic data mining tasks, such as data summarization, anomaly detection, associations and patterns mining, prediction and clustering. We focused on prediction and divided the prediction methods by their theoretical foundations (regression, time series analysis, artificial intelligence). In the forecasting overview, we mentioned the division of the forecasting methods to subjective and objective ones, and the measures used for their evaluation.

In the second part, we focused on specific works in stream mining area, power engineering domain and short-term power demand forecasting. Data stream has similar properties as big data – (possibly infinite) volume, velocity and variety (data of various types or data changing over time). Therefore, the data should be analyzed as soon as they are collected. The main requirements for stream processing method are low time and memory complexity, single pass over data, and the ability to adapt to concept drifts. We based the analysis of current stream mining methods on the survey by Gama et al. [7], which defined the three steps of stream mining process (predict, diagnose, update) and divided the stream mining methods by approaches used in four parts of stream processing system diagram: memory, learning, loss estimation and change detection (see figure 1). It is the third step of the process (update) that addresses the need to adapt the prediction model in time. The second step (diagnose) is implemented in the change detection part, which alarms about concept drifts, which require model update. Based on the presence of explicit change detection mechanism,

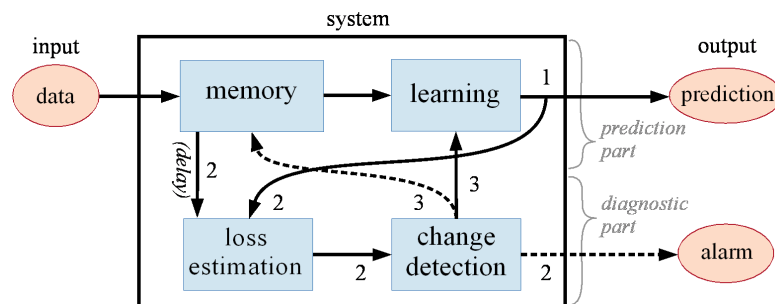


Figure 1: Stream data mining process [7] (1 – predict, 2 – diagnose, 3 – update; solid lines – mandatory steps, dashed lines – optional steps).

the adaptation can be divided into informed and blind. The blind adaptation updates the prediction model continuously, regularly without respect to the diagnostics.

Stream mining open problems specifies some of the big data open problems, they are related to privacy, variety and mostly to the human cooperation. The restrictions of stream processing (limited time, memory, concept drifts, ...) suggest that stream methods operate in a more complex way. Despite of this, the methods are supposed to be more understandable to humans and comfortable to utilize in practice. Therefore, the thorough evaluation and analysis of their properties, especially their ability to adapt to concept drifts, are essential.

In power engineering domain, the analysis was aimed at current changes in legislation related to smart metering introduction, the way the power is produced in Slovakia, how is the power demand estimated nowadays, and which factors influence the power demand. From the short-term standpoint, the demand is affected mostly by time of the day, day of the week, holidays and weather, especially temperature. It is sufficient to use historical power load records only for very short-term forecasts (up to 24 hours), because it is assumed that the demand depends only on the recent past and is not changing rapidly. The current trends and technologies in smart metering are subject of a number of both local and global conferences, e.g., *Smart metering*<sup>1</sup>, *Energetika*<sup>2</sup>, *Energofórum*<sup>3</sup>, *Elektroenergetika*<sup>4</sup>. The best power demand forecasting methods are regularly compared in competitions, such as M-Competition<sup>5</sup> and GEFCOM<sup>6</sup>.

Prediction methods divide into two big groups by their theoretical foundations – statistical and artificial intelligence. The pros and cons of both groups are summarized in table 1. They are often combined into hybrid methods. With the repopularization of neural networks at the beginning of this century, they became the most utilized artificial intelligence method, even in the power demand forecasting. From the adaptability point of view, the blind adaptation with a sliding window is mostly employed, i.e., a new prediction model is regularly trained on data from the sliding window. The training of a new model can be quite time-consuming and not always necessary. Informed adaptation based on concept drift detection can potentially improve prediction accuracy and spare computation and memory resources. Informed adaptation can besides historical power load records consider other data sources, e.g., weather, holidays, consumer behavior, and separate them from the prediction model. This can be advantageous if the other data sources are not available/updated all the time unlike smart metering data. When we analyzed existing power demand forecasting methods, we did not encounter an approach with an informed adaptation. That is why we focused on utilization of such approach in the design of our stream processing prediction method.

<sup>1</sup><https://konferencie.efocus.sk/konferencia/8.-rocnik-konferencie-smart-metering-smart-grid-nova-energetika-sme-na-nu-p>

<sup>2</sup><http://www.power-engineering.sk>

<sup>3</sup><http://www.energoforum.sk>

<sup>4</sup><http://seen.feituke.sk>

<sup>5</sup><https://www.mcompetitions.unic.ac.cy>

<sup>6</sup><http://www.drhongtao.com/gefcom>

**Table 1: Pros and Cons of Power Demand Forecasting Methods**

	<i>pros</i>	<i>cons</i>
<i>statistical</i>	<ul style="list-style-type: none"> <li>• easy interpretability</li> <li>• few parameters to estimate</li> <li>• better univariate models</li> </ul>	<ul style="list-style-type: none"> <li>• ability to model only linear relationships</li> <li>• low accuracy in longer term</li> <li>• statistical and domain knowledge required</li> </ul>
<i>artificial intelligence</i>	<ul style="list-style-type: none"> <li>• minimum statistical or domain knowledge required</li> <li>• ability to model also non-linear relationships between power demand and exogenous variables (e.g., weather)</li> <li>• better multivariate models</li> </ul>	<ul style="list-style-type: none"> <li>• difficult interpretability</li> <li>• over-parametrization</li> <li>• heavy computation without optimization</li> </ul>

### 3. Datasets

We used smart metering data from two countries: Slovakia and Ireland.

Slovak data were obtained in the project “International Centre of Excellence for Research of Intelligent and Secure Information-Communication Technologies and Systems”<sup>7</sup>. The data included smart measurements from all over the Slovakia from July 1, 2013 to February 16, 2015 (596 days). The measuring frequency was 15 minutes, most of the customers were small and medium enterprises. We divided the data into 19 parts by the region (according to the first two digits of postal codes). We filtered out the consumers without missing measurements and summated the consumption of each region (groups of 100 to 1,300 customers). In the end, we got 19 power load time series. We examined the series and selected four types of concept drift patterns (see figure 2). The data are described in more detail in publication [4].

Irish data came from Smart metering project of Irish regulatory office CER, that happened during 2007 to 2013 and its goal was to perform trials to assess the performance of smart meters, their impact on consumers’ energy consumption and the economic case for a wider national rollout. The data contained 30-minute measurements of approximately 5,000 households and small and medium enterprises<sup>8</sup>. We used aggregated power load time series of 3,639 without missing measurements. We chose two test sets: one month (September 20 to October 20, 2009) and six months (july to december 2010) long. These test sets were used in similar papers [13, 18]. The data were normalized to  $(0, 1)$ .

### 4. Incremental Power Demand Forecasting using Error-Driven Informed Adaptation

The adaptive prediction method for stream processing is based on the stream mining process, which consists of three steps: predict, diagnose, update (see figure 3). We

<sup>7</sup><http://ice-rise.sk/>

<sup>8</sup><http://www.ucd.ie/issda/data/commissionforenergyregulationcer/>

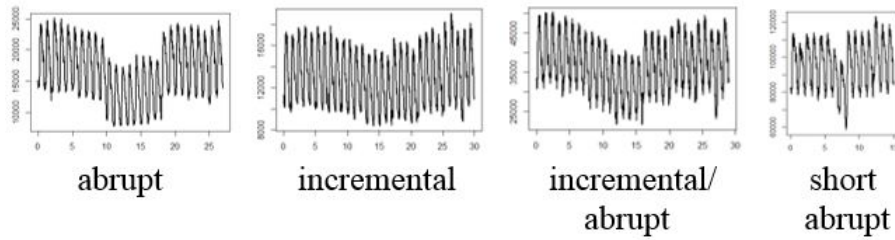


Figure 2: Concept drift types in Slovak power demand time series.

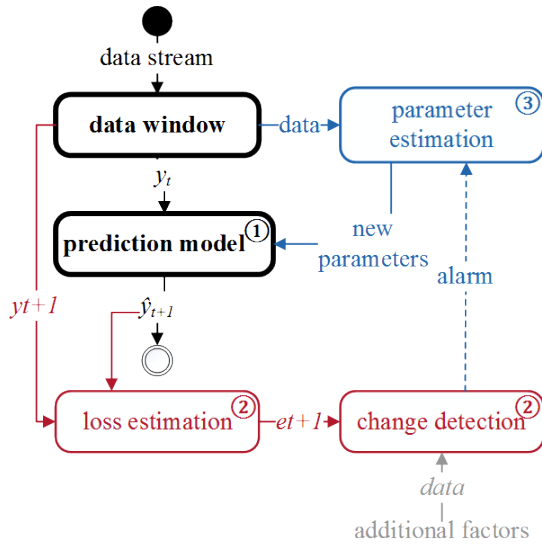


Figure 3: Abstract diagram of adaptive forecasting method consisting of 3 steps: 1 – predict (black), 2 – diagnose (red) and 3 – update (blue).  $y_t$  and  $\hat{y}_t$  are real and forecasted power load values,  $e_t$  is prediction error at time  $t$ .

chose double seasonal Holt-Winters exponential smoothing (DSWH) [16] as a prediction method, because of its simplicity, robustness and suitability for incremental processing as it is defined recursively. It can also model double seasonality (daily and weekly) of power load time series. DSHW also won in comparison with various prediction methods on European power load data [17].

Informed adaptation is based on monitoring of prediction error in time. The increasing prediction error suggests that prediction model becomes unsuitable for modeling of the incoming observations and it is necessary to update it. To detect changes in prediction error, we used the condition defined by equation 1. The change is detected when daily percentage error  $pe_t$  (for the last 24 hours, i.e., the last 96 15-minute measurements) exceeds 5%.  $e_t$  is prediction error and  $y_t$  is power load value in time  $t$ . The condition considers the specifics of power engineering domain, specifically the maximum acceptable 5% daily deviation of prediction from the actual power load and the fact that both positive and negative deviations are penalized.

$$pe_t = \frac{|e_{t-95}| + \dots + |e_{t-1}| + |e_t|}{y_{t-95} + \dots + y_{t-1} + y_t} \quad (1)$$

When a change is detected, the model is updated. To decrease the computing complexity, we decided not to update the whole model, instead we update only a part of its smoothing coefficients. We kept the coefficients related to daily and weekly seasonality, which were assumed not to change. The new coefficients were estimated from the most current data from the 2-week sliding window.

The precondition of our method is an initial prediction model trained on a longer chunk of data. This model is then continually monitored and updated.

#### 4.1 Evaluation

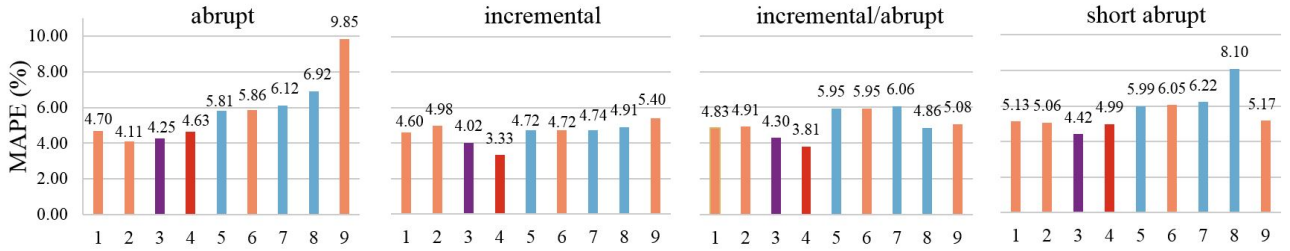
We evaluated the method by four experiments, which compared the performance of the method on data streams with and without concept drifts, incremental and batch processing, the performance of the method on various types of concept drift patterns with other commonly used methods and the performance of the method on various types of time series (outside power engineering domain). Slovak data were used.

The prediction accuracy of our method was not significantly different when we tested it on data with and without concept drifts. The method worked good in both cases.

The second experiment compared batch and incremental approach with the same prediction method. In the batch approach, the training set (all historical data) was at the end of each day supplemented with measurements from the current day and a new model was trained to predict the next 24 hours. We found out that incremental processing required approximately half the updates the batch approach needed and at the same time its accuracy was not significantly worse. It achieved comparably good accuracy with much smaller amount of training data (2-week sliding window) and updates.

In the third experiment, mean absolute percentage error (MAPE) was measured on four types of concept drift patterns. The results were compared with 8 incremental methods that used blind adaptation (daily model training on data from a sliding window). The comparison is displayed on figure 4. The accuracy of our method was significantly better than accuracy of some blindly adapting methods and it was similar to the accuracy of an ensemble model [4]. Our method worked best on incremental or incremental/abrupt concept drift patterns. The informed adaptation struggled the most with the abrupt concept drift pattern.

The purpose of the last experiment was to find out for which type of time series is our method the most suit-



methods: 1 – random walk, 2 – seasonal and trend decomposition by local regression+ARIMA, 3 – ensemble model [4], 4 – informed DSHW, 5 – random forest, 6 – multiple linear regression, 7 – SVR, 8 – multilayer perceptron, 9 – DSHW

**Figure 4: Comparison of incremental adaptive DSHW (no. 4) with 8 incremental blindly adaptive methods on 4 types of concept drifts. Blue columns are AI-based methods, the violet one is an ensemble model, the rest are statistical methods.**

able. We used data from M3 competition [14], which contain 1,428 time series with monthly frequency from six domains: micro, industry, macro, finance, demography a other. Our method did not excel in every domain, however, it worked well for macro time series. It is the most frequent type of time series, e.g., aggregated production, demand, prices data for regions, states, etc. Power demand also belongs to this type.

## 4.2 Discussion

The disadvantage of our method is that after the update of the prediction model, its diagnostics is again possible after 24 hours and great loss can occur during that time if the model update did not improve the accuracy. The prediction model should adapt more quickly and continually. Despite of this disadvantage, we consider the employment of informed adaptation in power demand forecasting as a contribution, since we did not encounter such approach in this domain yet and we showed its potential to achieve similar results as the batch approaches and to spare computing resources. Another challenge could be the investigation of detected concept drifts and their connection to events that might cause them. Because of the mentioned disadvantage, we focused on online methods in the next part of the thesis.

## 5. Smart Grid Load Forecasting using Online Support Vector Regression

Online stream processing, unlike incremental stream processing, processes data one-by-one without the necessity of their storage in a database or a sliding window. From the adaptation standpoint, the model changes continually, after processing of each instance, without change detection mechanism, i.e., blindly.

As a prediction method, we chose support vector regression (SVR). Its short-term forecasts are very accurate (also in power demand forecasting) and it often outperforms neural networks [1, 9, 10, 15, 18]. SVR tries to find such function with  $\epsilon$  margin, so most of the instances are covered (modeled) by it. Instances that lay on the edge of the margin are called support vectors. The distance of instances outside the margin (outer vectors) from the margin is penalized by cost  $C$ . Based on these principles we can define conditions for each group of vectors in the SVR model: inner, support and outer vectors. If a function with a margin can not be found, a kernel trick (function) is used. The instances are transformed into a space with more dimensions where such function exists.

One flaw of SVR is its inability to forecast more than one value ahead. To forecast a longer horizon, multiple simultaneous SVR models must be used. To estimate suitable SVR parameters ( $\epsilon$ ,  $C$  and parameters of kernel function), biologically inspired optimization algorithms are utilized.

Online version of SVR has been already published in 2000 [5], but even nowadays it is not well-known, mostly because there is no standard library implementation. The method tries to assign each new instances (vector) to one of three vector groups so it satisfies the group's conditions. If it is not possible, the vectors in model migrate between groups until there is found a space for the new vector. There are three types of allowed migrations between groups (see figure 5). The maximum number of vectors in model is limited by a *threshold*. The algorithm of online SVR training is stated below (see algorithm 1).

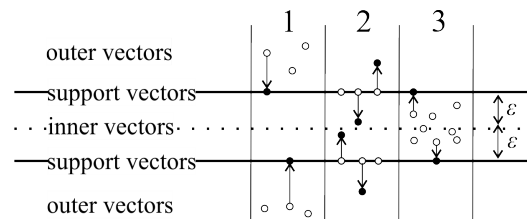
### Algorithm 1: Online SVR training.

Vector removal (2-5) and vector addition (6-12).

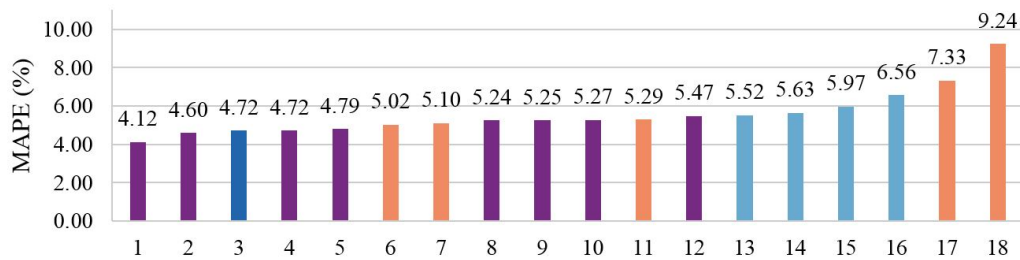
```

1 if model contains threshold number of vectors then
2   until weight of the oldest vector is not minimum do
3     find vector with minimum weight in model
4     update (migrate) the vector
5     remove the oldest vector
6 add new vector to SVR model
7 if it is an inner vector then
8   end of action
9 else
10  until the vector is not support or outer vector do
11    find minimum needed updates (migrations) of
      vectors in model
12  update model vectors

```



**Figure 5: Geometric representation of possible vector migrations. 1 – from outer to support, 2 – from support to inner or outer, 3 – from inner to outer vectors.**



methods: 1 – random forest\*, 2 – bagging, 3 – online SVR, 4 – extremely randomized trees\*, 5 – bagging\*, 6 – DSHW, 7 – seasonal and trend decomposition by local regression (STL)+ARIMA\*, 8 – extreme gradient boosting\*, 9 – extreme gradient boosting, 10 – extremely randomized trees, 11 – STL+exp. smoothing\*, 12 – random forest, 13 – SVR\*, 14 – SVR, 15 – deep learning, 16 – multilayer perceptron, 17 – STL+ARIMA, 18 – STL+exp. smoothing

\*separate workday/weekend model

**Figure 6: Comparison of online SVR (no. 3) with 10 forecasting methods with sliding window, one-day ahead forecast on 6-month test set. Blue columns are AI-based methods, the violet ones are ensemble learning models, the rest are statistical methods.**

## 5.1 Evaluation

We evaluated the method by six experiments. We compared its accuracy with standard SVR, examined its accuracy when various kernel functions were used, evaluated accuracy of very short-term and short-term forecast, compared its accuracy with selected traditional prediction methods, explored the optimization of its parameters by biologically inspired optimization algorithms, and evaluated its computing and memory complexity. We used Irish data in these experiments.

We found out that online SVR has the same accuracy as standard (batch) SVR. The best results for power demand forecasting are achieved when radial basis function is employed as the kernel function.

In the third experiment, we forecasted 30 minutes and one hour ahead for one month and for six months. We evaluated mean absolute percentage error (MAPE) and found out that the error lowers with increasing number of vectors in model, i.e., the longer the model forecasts, the more accurate it is. We achieved similar results (MAPE approx. 2.5%) as a similar existing method [18].

The fourth experiment was aimed at one-day ahead forecast for six months. We used 48 simultaneous online SVR models (one for each half-hour). The forecast error was compared with other 10 methods that utilized a sliding window. We also tried separate workday/weekend models for 7 methods. The results are shown on figure 6. Online SVR method achieved the third best accuracy. The best methods were based on ensemble learning (random forest, bagging, extremely randomized trees) and contained hundreds or thousands of decision trees. Quite good accuracy was achieved by statistical methods based on time series analysis that considered double seasonality.

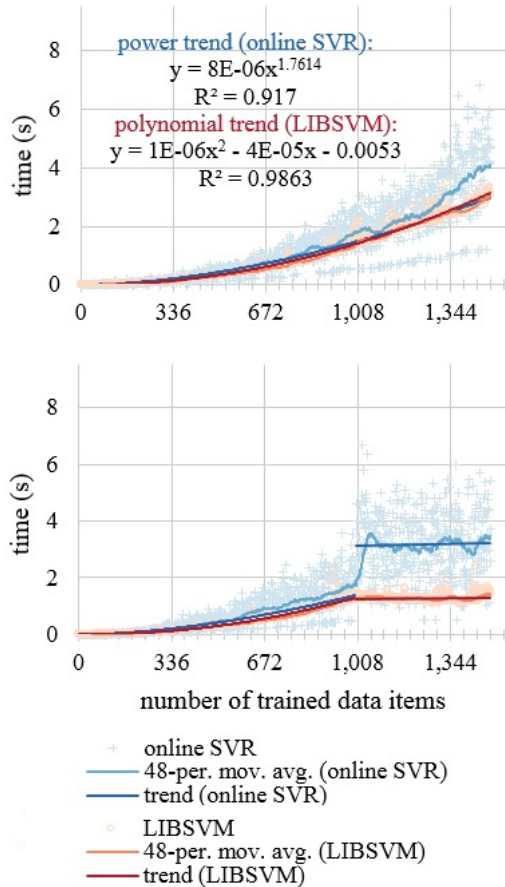
We compared online SVR to a similar work that used the same one-month test set [13]. OS-ELM method clustered similar consumers at first, then forecasted the consumption of each cluster and finally summated the forecasts. It utilized weather data in prediction as well. Average and maximum MAPE of the method was 2.47% and 4.21%. The results of our method were 3.00% and 4.01%. On average, online SVR was worse, but its error did not increased over time dramatically and behaved quite stable.

To estimate the parameters of SVR ( $\epsilon$ ,  $C$  and parameters of radial basis function) we employed particle swarm optimization (PSO). In the fifth experiment, we examined whether the accuracy can be further improved by utilization of other optimization method. We chose cuckoo optimization algorithm (COA). We let the models with optimized parameters forecast for five times on one-month test set. We discovered that parameters optimized by COA significantly lowered the forecast error (by 0.02%). The time of optimization by both of the algorithms was almost identical.

The last experiment evaluated the time and memory complexity of online SVR and compared it to standard (batch) SVR from LIBSVM library [6]. We found out that the time complexity of both methods is  $O(n^2)$  to  $O(n^3)$ . Measured training times on one-month long test set are shown on figure 7. The duration of a new vector addition to the model depends on the number of vectors that have to migrate in order to find place for the new vector. If the new vector belongs to the inner vectors, the training time is very low (see the light blue curve in the bottom of upper graph in figure 7). If the maximum number of vectors in model is limited by a *threshold*, training time oscillates around mean value and the ascending trend stops. The training time also depends on the length of the vectors – the longer the vectors, the longer the training time. On the other hand, the forecast error of SVR model with longer vectors and higher *threshold* was lower. Memory complexity of online SVR depends on the number of vectors in model (i.e., on *threshold*). To create a new vector it is also necessary to keep in memory a sliding window of size of a vector. Batch SVR needs to keep in memory *threshold* number of observations, since it is always trained on all historical data from scratch.

## 5.2 Discussion

The disadvantage of online SVR is that if we want to forecast a longer horizon at once, a separate SVR model must be used for each forecasted period, because the method has only one output. Iterative strategy or reformulation of the SVR model to multiple outputs, e.g., [3], could improve its accuracy. Other possible improvements leading to lower forecast error are inclusion of other data sources (e.g., weather), a kernel function designed specially for our data, usage of other optimization algorithms for SVR pa-



**Figure 7: Comparison of online and batch (LIBSVM) SVR training time. Measured times, 48-period moving average and trendline.  $threshold = 2000$  (up) and  $threshold = 1000$  (down).**

rameters estimation or clustering of consumers into similar groups before forecasting.

## 6. Conclusion

In this thesis, we analyzed areas related to predictive analysis on data streams, such as big data, knowledge discovery from data, forecasting or stream mining. The thesis is set in the power engineering domain and we focused on power demand forecasting. Our task was to create a short-term forecasting method of power demand of a group of consumers. The main motivation was the fact that inaccurate forecasts cause big deviations in power grid, which is damaged by them, and power suppliers are financially penalized for causing deviations by a regulatory office. The improvement of forecasts in Slovakia by 1% could lower the regulatory fees by millions of euros. The introduction of smart meters caused that much more data is generated than it was available until now, and therefore provided data for more accurate forecasts. That is why there emerged a need for transition from standard batch data processing to stream processing.

Data stream has similar properties as big data – *volume*, *velocity*, *variety*. According to these properties, we identified the main requirements for stream prediction method, i.e., *accuracy*, *timeliness* and *adaptability*. We put emphasis on *usability* of the method in practice, which is one of

the very often mentioned open problem of big data and stream processing. In power engineering, these properties project in endless streams of measurements from a large number of smart meters. Regularly incoming power load values are influenced by consumers' behavior, weather, social events, etc. Requirements for power demand forecasting method are daily prediction error under 5%, known forecasts at least one hour ahead for electricity market trading purposes, and consideration of concept drifts in power load. Our task was one-day ahead power demand forecasting for a group of customers of one power supplier, i.e. a balancing group. Measurements from individual consumers were summated into one time series.

We looked at stream forecasting methods mainly from two standpoints – *data processing* and *adaptation technique*. We focused on incremental and online processing, which, unlike the standard batch processing, does not have to keep all historical data in memory. The most utilized approach is *incremental learning with partial memory*, usually a sliding window. After each slide of the window, the prediction model is trained on data from the window. Therefore, the model develops in time and accomodates some degree of adaptation. Since the adaptation happens independently from the changes in data (concept drifts), it is also called *blind adaptation*. On the other hand, *informed adaptation* is based on explicit change detection, otherwise it does not happen at all. This way of adaptation can be more suitable in cases, when concept drifts are not very frequent or distinct and regular blind adaptation would not bring anything new to the prediction model.

In this thesis we studied two forecasting methods – *incremental with informed adaptation* and *online with blind adaptation*.

We found out that informed adaptation needed significantly less computing resources than batch processing with blind adaptation and the accuracy did not significantly lower. This method is suitable for flow time series that measure activity over time, e.g., macroeconomic time series of aggregated variables, such as unemployment, industry production, export, import, etc. The time series of power demand of a larger group of consumers also belongs to this category. The disadvantage of informed adaptation was the required longer pause between two consequent concept drift detections. That is why we decided to explore online approach, which processes data in one-by-one fashion without keeping them in memory.

We showed that online forecasting method with blind adaptation is suitable for power demand forecasting and achieves the accuracy of ensemble models, which have in general much higher computing complexity. We evaluated its properties, pros and cons by a series of tests and our findings are further applicable in other application domains. At the same time, we compared a wider spectrum of power demand forecasting methods and provided a self-contained view on performance of forecasting methods in this area. We encountered in literature only a few similar reports, which compared more prediction methods, usually on private data sets.

Both of our approaches accomplished the daily forecast error under 5% and the accuracy of batch forecasting

methods. Their design is aimed at constant computing resources, which is an important aspect in big data processing, low number of method parameters, easy understandability and interpretability. We addressed the open problems we mentioned at the beginning: the need for transition from batch to stream processing, usability in practice and evaluation of stream mining methods.

In future, we want to focus on possible improvements of our approaches we mentioned in discussion sections of this paper, or on brand new forecasting methods with promising results, such as approaches based on analysis of patterns, which occur repeatedly in time series. These approaches can model well the various types of consumers or various concept drift patterns in power load. We would like to focus also on other smart grid components, e.g., photovoltaic panels, batteries, electric cars, which bring new open problems related to their optimal settings, localization, microgrid establishment, etc. The road to the future vision of smart grid must yet run through many legal, practical and research challenges.

**Acknowledgements.** This contribution was created with the support of the Research and Development Operational Programme for the project “International Centre of Excellence for Research of Intelligent and Secure Information-Communication Technologies and Systems”, ITMS 26240120039, co-funded by the ERDF; and the Slovak Research and Development Agency under the contract No. APVV-16-0213.

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