

# A PRELIMINARY BENCHMARK OF FOUR SALIENCY ALGORITHMS ON COMIC ART

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## ABSTRACT

Predicting the salient regions of a comic book panel has the potential to drive a variety of applications such as segmentation, cropping, effects such as moves on stills, etc. Computational saliency algorithms have been widely tested on a variety of natural images, and extensively benchmarked. We report the performance of four saliency algorithms on a set of comic panels taken from public domain legacy comics. We find that a data-driven method performs highest based on two metrics, Normalized Scanpath Saliency and Area Under the Curve. We discuss possible reasons for this finding based on an exploratory analysis of the similarity between the comic images in our dataset and images used in the dataset of the data driven method.

*Index Terms*— saliency, human gaze, predicting fixations, comic art

## 1. INTRODUCTION

Knowing the salient components in an image is useful for a variety of applications, such as compression, segmentation, auto cropping, etc. Comic artists and filmmakers use visual symbols as cues to lead the viewer’s attention [1]. Understanding saliency in comic art could illustrate design decisions such as effective color contrast, the placement of objects and word bubbles, captions, illumination, etc. The two widely accepted approaches to model visual saliency are bottom-up and top-down approaches. The former is a stimulus driven approach, according to which features in an image that are very distinguishable by the human eye stand out [2]. Top-down models take a task-driven approach, driven primarily by the goal of viewing the image, for example, finding all occurrences of a flower in an image, or, trying to memorize different terms of a human heart [3].

**Our contributions** We perform a comparative analysis of four saliency models on a set of comic panels taken from public domain legacy comics. These saliency models are a data-driven approach (LSVM) [4], a graph based bottom-up saliency model (GBVS) [5], a difference of gaussian based bottom up algorithm (VOCUS2) [6] and a region contrast

based salient object detection (RC) [7]. Our primary contribution is benchmarking these saliency models for comic art. We find that LSVM outperforms other three models on comic images. We discuss possible reasons for this, by exploring the similarity between comic art and natural images used by LSVM for training and testing.

## 2. RELATED WORK

Saliency modeling has been an active field of research. The earliest models used selective features at several image scales to form a bottom-up saliency map ([8], [9] and [10]). [5], [11], [12], [13], [14] are several approaches based on the bottom-up technique of modeling saliency. Top-down saliency is driven by tasks, rewards, emotions and expectations, as opposed to physical characteristics of bottom-up detection [15], [16], [17]. Recent advances in predicting fixations use deep neural networks [18], [19], [20], [21].

Based on consistent success over time, LSVM and GBVS form two natural choices for this benchmark study. VOCUS2 and RC have been chosen because they are recent models that report outperforming several other models in different applications. LSVM, a data-driven approach, combines low, mid and high level features, and trains a Linear Support Vector Machine on gaze data from multiple viewers, performing a free viewing task on several images. GBVS, a non data-driven approach, aims at exposing connected regions of dissimilarity, defined as the distance between the intensity of two pixels, measured on a logarithmic scale. VOCUS2, a derivative of the original, biologically inspired saliency model in [8] employs a pyramid structure consisting of twin pyramids with multiple scales per layer as opposed to one pyramid with one scale per layer used originally. RC [7] uses a graph-based image segmentation technique to form regions in an input image, and computes region level saliency by finding color contrast to all other regions in that image.

## 3. EYE TRACKING DATA ON COMIC IMAGES

Our comic dataset consists of 23 images, taken from public domain legacy comics. We recorded eyetracking data from

5 viewers (3 male), using a remote eyetracker (SensoMotoric Inc, SMI RED-m, 120 Hz). Participants were seated at a distance of approximately 64 cm from the screen (1680 × 1050) resolution, 18in×11in. A visual angle of 1 degree is approximately 37 pixels at these settings. Data consisted of fixations in the x and y space coordinates, event information comprising either of a ‘blink’, ‘fixation’, or, a ‘saccade’, along with the stimulus name, with corresponding timestamps. Figure 1 depicts a few samples from the comic dataset, where the gaze data of 5 subjects has been overlaid on the stimulus. Each subject’s fixations are marked in a different color. Samples where the gaze position was outside the screen were discarded.



**Fig. 1:** Gaze data from 5 participants shown as different colored circles on randomly chosen images from comic panels.

#### 4. BASELINE CHECK

To validate our test setup, we perform a comparative analysis for all four models over three image categories from the CAT2000 dataset [22]: Outdoor Man-made, Outdoor Natural, and Social. We perform experiments to evaluate the ability of models to predict ground truth human fixations. [23] reports the evaluation of submitted models with several metrics, such as, Similarity Measure (SIM), Earth Mover’s Distance (EMD), Pearson’s Linear Coefficient (CC), Normalized Scanpath Saliency (NSS), and different versions of Area Under Curve (AUC). Their results are based on their evaluation on all 20 categories and ground truth from 24 observers. We compare the performance of LSVM and GBVS on our 3 category test setup and compare the scores against those reported by [23] as a sanity check on our test setup.

Table 1 depicts mean NSS scores from our test setup and those reported by the benchmark. The overall NSS score is averaged across the 3 categories. Similarly, average AUC score for our experiments compared to benchmark values are reported for LSVM and GBVS as shown in the Table 2. Here, it should be noted that the scores from our test setup would not mirror scores from the benchmark [23], because the latter evaluates the models on test images and different observers,

**Table 1:** Mean NSS Scores reported by our test setup on three categories from natural images show similar trend when compared to the scores reported by [23] for the same image categories. Standard deviations are reported in brackets.

Our Test Setup				
Normalized Scanpath Saliency [NSS]	Outdoor ManMade	Outdoor Natural	Social	Overall
LSVM	1.22 (0.22)	1.28 (0.21)	1.21 (0.19)	1.24 (0.21)
GBVS	1.11 (0.28)	1.17 (0.34)	1.14 (0.27)	1.14 (0.3)

Benchmark Reported Scores				
Normalized Scanpath Saliency [NSS]	Outdoor ManMade	Outdoor Natural	Social	Overall
LSVM	1.27 (0.2)	1.23 (0.21)	1.18 (0.19)	1.23 (0.2)
GBVS	1.18 (0.34)	1.06 (0.36)	1.1 (0.32)	1.11 (0.34)

**Table 2:** Our test setup and the benchmark [23] report similar AUC scores for natural image categories namely, Outdoor Natural, Outdoor ManMade and Social.

Our Test Setup				
Area Under Curve[AUC]	Outdoor ManMade	Outdoor Natural	Social	Overall
LSVM	0.83 (0.04)	0.84 (0.04)	0.83 (0.05)	0.83 (0.04)
GBVS	0.79 (0.06)	0.79 (0.05)	0.79 (0.05)	0.79 (0.05)

Benchmark Reported Scores				
Area Under Curve[AUC]	Outdoor ManMade	Outdoor Natural	Social	Overall
LSVM	0.84 (0.04)	0.84 (0.04)	0.83 (0.04)	0.84 (0.04)
GBVS	0.8 (0.05)	0.78 (0.06)	0.79 (0.06)	0.79 (0.06)

whereas our test setup has been evaluated on the publicly available training data. The authors of RC [7] report a comparison of their model with LSVM, and based on the AUC score, LSVM is reported to outperform their model in predicting human fixations. Figures 5 and 6 show LSVM outperforms all other models on all four categories including comic, based on both NSS and AUC scores per our evaluation too.

## 5. EXPERIMENT

To evaluate the performance of the four saliency algorithms, we use code made available by the authors with default settings. We obtain saliency maps for all 23 comic images. Figure 2 shows saliency maps for six chosen comic panels. Comic panels 2, 6 and 8 are selected based on their high NSS scores for all four models ( Figure 4 ). It is observed that almost all saliency algorithms show relatively low performance for comic panels 7, 14 and, 20. These panels illustrate certain comic images are difficult to detect visual attention with the models in our test setup. Figure 2 depicts regions marked salient by each model on these specific images.

### 5.1. Performance Analysis

The eyetracking data is overlaid on the comic images resized to the same resolution at which they were displayed at, for data collection from five subjects. Once we obtain the

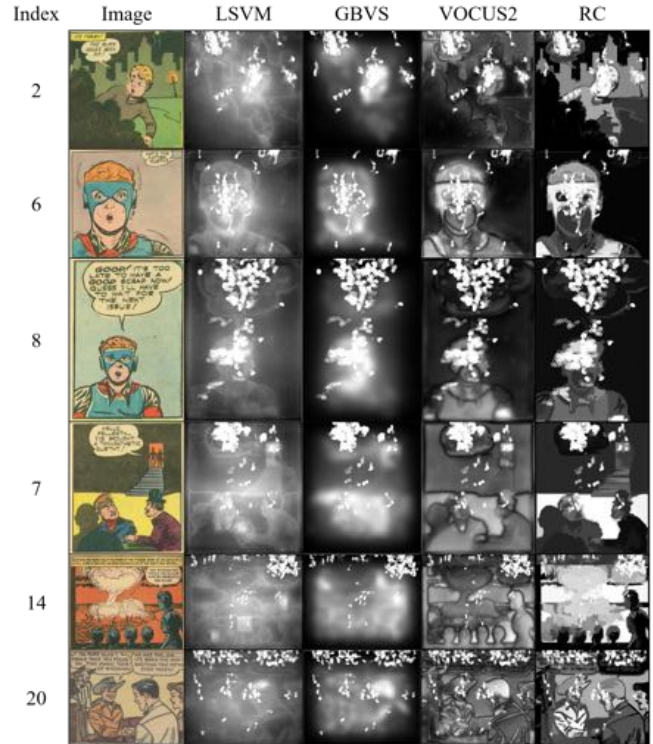


**Fig. 2:** Saliency maps generated from four different algorithms are depicted for chosen comic images. LSVM, GBVS show center bias, and similar regions are marked salient. VOCUS2 finds it difficult to detect multiple salient regions, whereas, RC marks complete regions as salient.

saliency maps from all four models for 23 images from comic dataset, next, we overlay the fixations on the saliency maps as shown in the Figure 3.

To evaluate the performance of each model on comic images, we use Normalized Scanpath Saliency (NSS), as described in [24]. Each saliency map was linearly normalized to have zero mean and unit standard deviation. The normalized saliency values were extracted corresponding to the fixation locations for each subject, and the mean of these values was taken as a measure of the correspondence between the saliency map and scanpath. For each model, mean of all the five subjects' NSS score results in the average NSS score for an image. The same is repeated to compute the mean NSS score for all four models across 23 comic images.

Figure 4 depicts the mean NSS score variation for each model, per image. It is interesting to note similar trends in performance across all models for comic images 2, 6 and 8, as well as 7, 14 and 20. Most models perform well in images 2, 6 and 8, whereas, they find it difficult to detect saliency in images 7, 14 and 20. We observed that GBVS shows peak performance at many instances, which are very close to the values of LSVM. However, LSVM outperforms GBVS, on an average across 23 comic images as shown in black bars and



**Fig. 3:** Gaze data from 5 participants is overlaid using white circles on the saliency maps generated from LSVM, GBVS, VOCUS2 and RC to show the overlap between where humans looked and the regions predicted by the saliency algorithms.

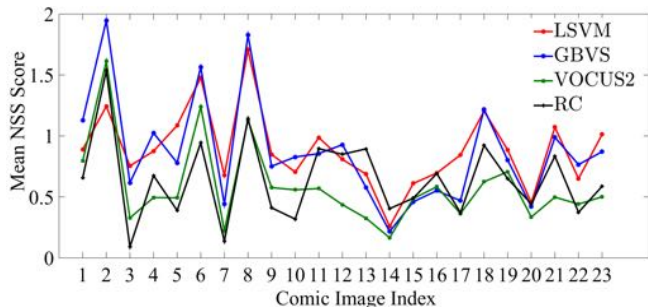
dark gray bars respectively in Figure 5 . We repeat the same experiment for three natural image categories from CAT2000 dataset. Figure 5 depicts an overview of performance of all four models in terms of mean NSS score.

We also report the performance of the models using another metric, Area Under the Curve (AUC). We use the implementation by [25] which requires a binary fixation map. For comic dataset, the raw data has fixations coordinates:  $x$  and  $y$  for each stimuli. We create a binary map with 1 corresponding to the fixation locations and 0 corresponding to the background locations . The scores reported from these experiments are also shown in Figure 6 . As shown in black bars, LSVM consistently outperforms all other models. GBVS is only marginally below LSVM as observed from dark gray bars. We observe that VOCUS2 performs the lowest, while RC is only marginally better than VOCUS2 for both NSS and AUC scores across all categories.

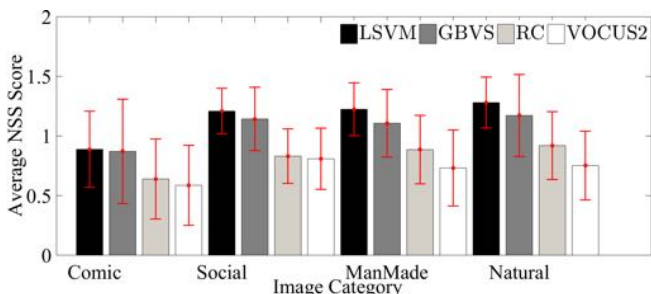
## 6. EXPLORATORY ANALYSIS

Our goal is to explore possible reasons for LSVM performing so well on comic images, when it is a data-driven model trained on natural images that (on the first glance) are not “comic like” in style. LSVM was never trained on comic im-





**Fig. 4:** Mean NSS Scores across 23 images. Comic images 2, 6 and 8 reported a relatively higher NSS scores for all models, whereas, consistent low NSS scores were observed for comic images 7, 14 and 20.



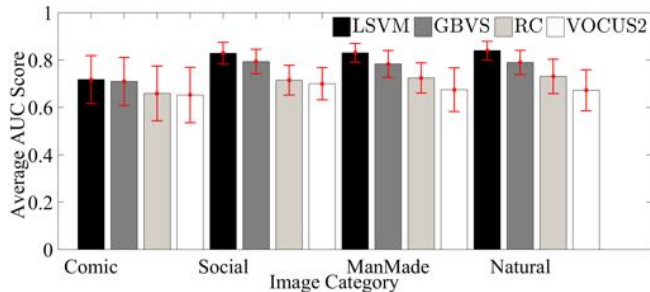
**Fig. 5:** Mean NSS score where error bars are standard deviation. LSVM consistently outperforms GBVS, RC and VOCUS2. Performance on natural image categories is relatively higher than that on comic images for all models.

ages, yet it outperforms all the other approaches for predicting fixations, not only in context of natural images, but also, for comic art. We present our hypothesis and experiments as supporting evidence to discuss possible reasons.

**Hypothesis 1: Comic panels in our dataset are similar to natural images in LSVM’s dataset [4] in terms of features used for saliency prediction.**

We consider the weights assigned to each of the 33 feature channels in LSVM’s model of saliency. We sort these weights. The most weighted features are the coefficients of the second coarsest sub-band of steerable pyramids [26], Viola Jones face detector [27], features used in a saliency model described by Torralba [28] and Rosenholtz [29], and color contrast as calculated by Itti and Koch’s saliency method [12], in decreasing order of the weights.

We use the implementation in LSVM to compute feature vectors for 1003 images from the LSVM dataset and 23 images from our comic dataset. We compute the distances between comic and natural images in feature space, using Euclidean distance. Each element in the resulting  $23 \times 1003$  matrix holds the pairwise distance score. These scores are averaged across all comic images, resulting in a  $1 \times 1003$  vector.



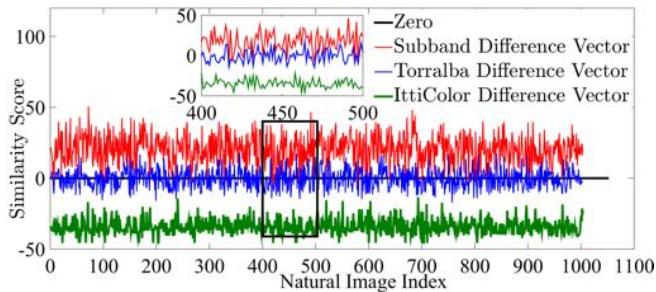
**Fig. 6:** Mean AUC score with error bars as standard deviation. Across all image categories, LSVM is ranked on top, followed by GBVS, RC and VOCUS2, in decreasing order of accuracy. Of the 4 image categories, all models are reported to show relatively lower performance on comic images.

This represents the average distance between comic and natural images, based on the feature being considered. Similarly, we compute pairwise distances between natural images which are then averaged across all natural images, resulting in a average distance vector of  $1 \times 1003$  dimension. To quantify similarity between comic images and natural images in a particular feature space, we define a similarity score which can be expressed as,

$$\text{Similarity Score} = (\text{Average distance between natural images}) - (\text{Average distance between natural and comic images})$$

With this definition, a high positive score indicates comic images were relatively more similar to natural images than the amount natural images are similar to other natural images. This is observed in context of using the second coarsest sub-band from steerable pyramids as the feature, based on the Figure 7. A low positive score is indicative of the fact that comic images are as similar to natural images as natural images among themselves. Similarly, a negative score depicts high dissimilarity between comic and natural images as compared to natural images. The latter is observed when color contrast as calculated by Itti and Koch’s saliency model [12] is used as the feature.

In other words, LSVM is expected to perform relatively the same on comic images as it does on natural images, if the similarity score is a high positive in accordance with our metric. This could explain why LSVM outperforms the other three saliency models that we benchmarked. It turns out that comic images are quite similar to natural images based on the features used by this model. These are preliminary findings because we have only studied 3 of the 33 features and only 23 comic images, but they could point to interesting future work directions. It will be interesting to perform the same experiment on manga images for example.



**Fig. 7:** High positive score using second coarsest sub-band from steerable pyramids as feature, shows higher similarity between comic and natural images, relative to the similarity among natural images. Low positive score indicates similarity between comic and natural images is of the same order as among the natural images, in context of features from Torralba saliency. The plot below the zero line, indicates comic images are lot different from natural images relative to the pool of natural images, in context of color channel as feature.

**Hypothesis 2: Face detection algorithms used by saliency models work well for natural images but not for comic art.**

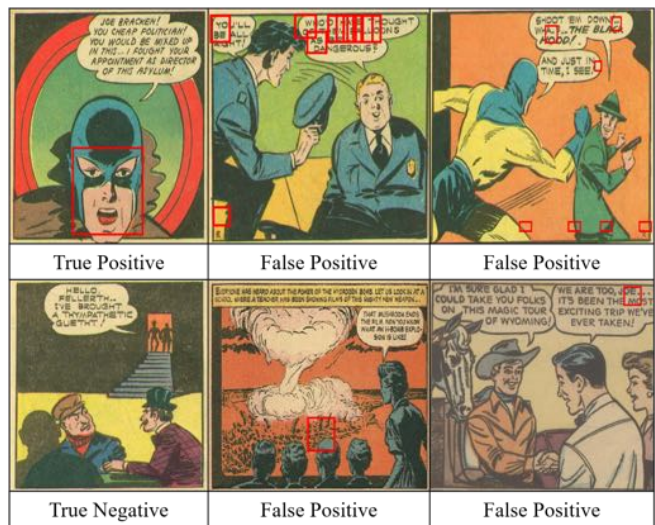
Our results and analysis indicate that all four models including LSVM show relatively poor performance for comic art, as compared to the performance of the the same model on natural images ( Figures 5 and 6 ). To understand this finding further, we study features which are highly weighted in LSVM’s saliency algorithm, in particular, faces. Faces are not only the second highest weighted feature, but also, one of the most gazed upon objects in an image [4].

We compute the accuracy of face detection for comic images, using the Viola Jones face detector [27]. The ground truth was marked by a human coder. Of the 40 faces in comic images, 7.5% faces were correctly detected, whereas 72.5% faces were false positives. Figure 8 shows a few samples from this experiment. From these results, we observe that the face detection fails for most of the comic images. This indicates that faces could be a potential reason for much lower performance of LSVM on comic art as compared to it’s performance on other natural image categories.

**6.1. Conclusion**

In this paper, we benchmark four saliency algorithms on comic images. We perform a comparative analysis of these algorithms in detecting salient regions in comic panels with eyetracking data. We find that a data-driven approach, LSVM, outperformed three other saliency models included in our test setup. We discuss potential reasons for these findings.

Evaluation of deep learning based saliency detection algorithms for predicting fixations could provide a deeper understanding of visual attention in comic art. It would be interesting to see performance of deep learning tools as they are free from hand-crafted features. Improving existing saliency



**Fig. 8:** Of the 40 faces in comic image data set, only 3 faces were detected correctly by Viola Jones face detector, whereas 29 detections were false positives. Faces in comic art are a lot different than those in natural images in style.

algorithms to detect visual attention in comic panels could be a promising direction for future work.

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