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ACM
2021

Kropotov , I , Medlar , A & Glowacka , D 2021 , Exploratory Search of GANs with Contextual Bandits . in Proceedings of the 30th ACM International Conference on Information &
þÿ K n o w l e d g e   M a n a g e m e n t .   A C M ,   p p .   3 1 5 7   3 1 6 1   ,   A C M   I n t e r n a t i o n a l   C o n
Information and Knowledge Management , Gold Coast , Australia , 01/11/2021 . https://doi.org/10.1145/3459637.348

http://hdl.handle.net/10138/352576
https://doi.org/10.1145/3459637.3482103

unspecified
acceptedVersion

Exploratory Search of GANs with Contextual Bandits

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ABSTRACT

Interactive image retrieval involves users searching a collection of images to satisfy their subjective information needs. However, even large image collections are finite and therefore may not be able to satisfy users. An alternate approach would be to explore a generative adversarial network (GAN) and model users' search intents directly in terms of the latent space used by the GAN to generate images. In this article, we present a simulation study exploring the performance of Gaussian Process bandits in the context of interactive GAN exploration. We used recent advances in interpretable GAN controls to investigate the scalability of different approaches in terms of image space dimensionality. While we present several experiments with promising results, none of the approaches tested scale sufficiently well to explore the entire GAN image space.

CCS CONCEPTS

• **Information systems** → **Image search**; • **Computing methodologies** → *Reinforcement learning*.

KEYWORDS

GANs; image search; interactive search; exploratory search; Gaussian Process bandits

ACM Reference Format:
Ivan Kropotov, Alan Medlar, and Dorota Glowacka. 2021. Exploratory Search of GANs with Contextual Bandits. In *Proceedings of the 30th ACM International Conference on Information and Knowledge Management (CIKM '21), November 1–5, 2021, Virtual Event, QLD, Australia.* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3459637.3482103

1 INTRODUCTION

Generative adversarial networks (GANs) are a framework for estimating generative models [13]. A GAN is composed of two networks that are trained jointly: a generator, that learns to generate synthetic data with the same distributional properties as the training data, and a discriminator, that learns to distinguish between synthetic and real data. A majority of GAN research is centered around synthetic image generation and recent work has resulted in GANs capable of generating high quality images, even at high resolutions [21, 23, 24]. While there are many techniques to manipulate the images generated by a GAN, the problem of how to perform interactive image retrieval over the GAN's image space has largely been ignored.

Interactive image retrieval involves users searching through images to satisfy their subjective information needs [26]. Given that the images generated by a GAN are defined by a continuous latent space, referred to as $\mathcal{Z}$ space, this might allow us to capture users' search intents better than a discrete collection of images. Approaches based on exploration–exploitation tradeoff [7, 9, 33, 41, 46], including bandit algorithms [5, 14, 17, 19, 27], have been shown to perform well in interactive intent modeling in image and multimedia search. Unfortunately, GANs present numerous challenges to the application of bandit algorithms in an interactive search setting: (i) there is no clear mapping between latent dimensions and semantic features, (ii) the dimensions of the latent space are entangled, and (iii) the number of unique images that can be generated is exceptionally high. These issues are not present to the same extent in other domains where bandit algorithms have been used to successfully model search intent, such as in exploratory search of scientific literature [29], where the datasets and features are usually static and pre-defined .

Two recent developments, however, suggest that bandit algorithms could be used to perform exploratory search of the GAN image space. First, Härkönen et al. show that principal component analysis (PCA) can be used to create interpretable GAN controls to alter, for example, the gender, age or pose of a generated face [15]. Second, Ukkonen et al. [42] show that relevance feedback can be used to explore a GAN using Rocchio's algorithm [35] to perform a local, greedy search of the underlying image space. We took inspiration from these two papers to investigate whether bandit algorithms can be used to perform exploratory search of a GAN's latent space. We present preliminary results from a simulation study comparing the performance of Gaussian Process (GP) bandits [10, 40] to Rocchio's algorithm in exploratory image search. In this paper, we present the following contributions:

- To our knowledge, we present the first study of using bandit algorithms to search a GAN's image space.
- We show that GP bandits ties with or outperforms Rocchio in a majority of experimental settings, but was too computationally intensive to search the full GAN image space.
- We demonstrate that neither of the methods investigated converge when searching > 10 principal components, suggesting that systems based on these approaches may struggle to satisfy users' information needs.

2 RELATED WORK

We briefly review related research in GAN manipulation techniques and the use of bandit algorithms in information retrieval.

CIKM '21, November 1–5, 2021, Virtual Event, QLD, Australia

ACM ISBN 978-1-4503-8446-9/21/11…$15.00
https://doi.org/10.1145/3459637.3482103

2.1 GAN Architectures and Manipulation

Research into GANs initially focused on improving the quality of generated images and the stability of training. For example, DCGAN uses convolutions in both the generator and discriminator [34], PCGAN progressively grows its architecture, and therefore the resolution of images, during training [21] and BigGAN introduced the "truncation trick", where images are generated by sampling from a truncated normal distribution [6]. More recently, StyleGAN [23] and StyleGAN2 [22, 24] used many of the same techniques as above together with a further intermediate latent space, called $\mathcal{W}$ space, that contains less entangled features.

Images generated by GANs can be manipulated by transforming a latent code in either the original latent space $\mathcal{Z}$ or $\mathcal{W}$ space by adding a vector for a given semantic feature, such as age, gender or facial expression. These vectors are often referred to as interpretable directions or controls. Interpretable controls can be created in a supervised manner [2, 18, 38], however, such approaches are constrained by the variety of available labels and tend to be biased due to multicollinearity of features. There are also unsupervised approaches to finding interpretable controls. Härkönen et al. create controls by sampling $\mathcal{Z}$ space and performing PCA on an intermediate representation of the GAN ($\mathcal{W}$ space in StyleGAN or feature space in BigGAN) [15]. Shen et al. show that unsupervised controls could be created without sampling, using closed-form factorization of network weights [39]. Other approaches for unsupervised discovery of interpretable controls are also being developed (e.g. [43, 44]).

Many other methods have been proposed for manipulating or editing images generated by GANs, such as using style transfer techniques [1], methods that involve drawing directly on an image [1, 50] and combining features from different images [8, 31]. For a comprehensive survey of GAN manipulation methods, we recommend the recent survey by Xia et al. [47].

2.2 Bandits in Information Retrieval

Over the last two decades bandit algorithms have been gaining popularity in various applications related to information retrieval and recommender systems [12]. Bandits have been successfully applied in many areas of information retrieval, including, the learning to rank problem and modeling user click behavior [16], result diversification [48], query auto-completion [45] and online ranker evaluation [51].

Bandit algorithms allow a system to trade off exploration (acquiring new information about the the search interest of the user) and exploitation (using existing knowledge about user's search interests). This characteristic makes bandit algorithms particularly suitable in areas such as exploratory search [28], where users have open-ended or ill-defined search goals that can gradually shift over a search session [5, 29, 30]. Additionally, bandit algorithms can be combined with relevance feedback [36] to allow incorporation of user's interests and preferences that further facilitate user intent modeling [3, 49]. At the same time, the exploration–exploitation tradeoff forming part of bandit algorithms prevents users from getting stuck in a context trap, which is often associated with traditional relevance feedback approaches [25].

In this study, we investigated using Gaussian Process bandits to perform exploratory search of a GAN's latent space. To our knowledge, the only work in this area used relevance feedback [42] and, therefore, the problem could benefit from the additional exploration performed by a bandit-based approach.

3 METHODOLOGY

In this section, we provide a brief overview of image generation in StyleGAN2, describe both Gaussian Process bandits and Rocchio's algorithm, and outline our simulation procedure.

3.1 Image Generation in StyleGAN2

We used StyleGAN2 [24][1] to generate images of faces using a pretrained model[2] based on the Flickr-Faces-HQ (FFHQ) data set [23]. StyleGAN2 has a special generator structure which consists of a mapping network f and a synthesis network g. To generate an image, a latent vector z is sampled from a distribution (typically multivariate normal) and mapped to an intermediate latent vector w using the mapping network f. Finally, w is fed to the synthesis network g to produce an image I. More formally, the image generation process can be described as $I = g(f(z))$, where $z \sim P(z)$. As not all areas of $\mathcal{W}$-space produce high quality images, StyleGAN2 uses the truncation trick to constrain w to be closer to the mean vector according to $w' = \bar{w} + \psi(w - \bar{w})$. This technique greatly improves the quality of generated images, but reduces image variety. We set the truncation parameter to $\psi = 0.5$, as it provides high quality images without loosing too much variation.

Unfortunately, $\mathcal{Z}$ and $\mathcal{W}$-space are not very useful on their own for controlling the appearance of generated images because their dimensions do not correspond to semantically meaningful features. We therefore used the method proposed by Härkönen et al. [15], where interpretable directions in latent space are found using PCA. In brief, we sampled 10^6 z-vectors, transformed them to $\mathcal{W}$-space and then computed PCA. We did not restrict the usage of the obtained latent vectors to a subset of network layers, as is proposed in the original paper, but use PCA-space directly as a surrogate search space instead of $\mathcal{Z}$ or $\mathcal{W}$-space. When searching PCA-space, instead of choosing w directly, we choose a vector x in PCA-space and transform it back into $\mathcal{W}$-space using inverse PCA.

3.2 Gaussian Process Bandits

As shown in the original StyleGAN paper, latent vectors that are close to each other produce similar images [23], which implies that such images would also get a similar reward from a user. Thus, we assume that the reward landscape is sufficiently smooth and use Gaussian process (GP) regression to predict the reward associated with images, using principal components as features. Gaussian processes are fully defined by their mean and covariance (or kernel) functions, $\mu(x)$ and $\kappa(x, x')$, respectively, which can be chosen to reflect prior knowledge. In our application, we used Matern kernel with the following parameter settings: nu = 2.5, alpha = 1e-6 (as in [32]). Matern kernel is a generalisation of the RBF kernel and is often used in applications related to spatial statistics and image analysis. The strength of using GP regression lies in its ability to model the uncertainty of predictions as variance. This enables the use of upper confidence bound (UCB) methods [4], where the

[1]https://github.com/NVlabs/stylegan2-ada-pytorch

[2]https://nvlabs-fi-cdn.nvidia.com/stylegan2-ada/pretrained/ffhq.pkl

search is focused on areas with the best potential. We used the UCB algorithm for Gaussian processes called GP-UCB [40].

The problem definition in GP-UCB is similar to the case of independent arms. We attempt to sequentially optimize a reward function $f : \mathcal{X} \to \mathbb{R}$, where $\mathcal{X}$ is the input space. This is done by choosing a point $\boldsymbol{x}_t \in \mathcal{X}$ and evaluate the result $y_t = f(\boldsymbol{x}_t + \epsilon_t)$ at that point. The goal is to maximize the sum of rewards.

In order to utilize the information of function values at the sampled points, we also have to take into account the mean values of the GP regression. Always selecting the information gain maximizer would be an exploration only strategy, while selecting points $\boldsymbol{x}_t = \mathrm{argmax}_{\boldsymbol{x} \in D}\, \mu_{t-1}(\boldsymbol{x})$ would be pure exploitation and would likely get stuck in a local optima. These two approaches can be balanced by choosing

$$\boldsymbol{x}_t = \underset{\boldsymbol{x} \in D}{\mathrm{argmax}}\, \mu_{t-1}(\boldsymbol{x}) + \beta \sigma_{t-1}(\boldsymbol{x}),$$

where β are appropriately chosen constant balancing factors for exploration-exploitation tradeoff. This objective greedily selects both points where reward is expected to be high and the uncertainty of the reward is large. In our experiments, we used $\beta = 0.9$ (identified from manual inspection, data not shown). We implemented GP-UCB with the Bayesian Optimization Python library [32].

3.3 Rocchio's Algorithm

We used the variant of Rocchio's algorithm introduced by Ukkonen et al. [42] as a baseline to compare with GP-UCB. In this context, Rocchio's algorithm maintains a centroid, c, in latent space and at every iteration samples vectors close to c. The sampled images are shown to the user, who provides relevance feedback. The feedback is used to update c so that it moves closer to relevant images and further away from irrelevant ones. Following Ukkonen et al., we sampled from a multivariate normal distribution with a scale parameter, σ, around the centroid and presented five candidate images at once. Ukkonen et al. only used positive relevance feedback, which simplifies the centroid update rule to $c_i = (1-\alpha)c_{i-1} + \alpha\, v_{avg}$, where v_{avg} is the average latent vector of images that received relevance feedback. The parameters used for experiments were $\sigma = 0.2$ and $\alpha = 0.7$ (as in [20]). We performed experiments in $\mathcal{Z}$ space like the original paper and PCA-space.

3.4 Simulation Procedure

3.4.1 User Model. We simulated users performing exploratory image search. We assumed that users would (i) have a particular target image in mind and (ii) be capable of assessing the distance between the target image and the candidate images presented to them. In each simulation, a target image is chosen at random from the search space (either $\mathcal{Z}$ or PCA-space) so the exact target image can potentially be found. This is important because in some experiments we restrict the search space to the first n principal components. We calculated the distance between faces with the Python Face Recognition library [11] that uses an approach similar to FaceNet [37]. We defined a threshold distance of 0.1 whereby images were considered "close enough" to the target image to have converged.

3.4.2 Rocchio's algorithm. For experiments with Rocchio, at each iteration we sampled 5 images and selected the closest image to the target for relevance feedback (i.e. $v_{avg} = v_{best}$). The search continues until an image close enough to the target is found or for a maximum of 80 iterations (showing the user a maximum of 400 images). With Rocchio, we ran experiments with and without warm start. Without warm start, the initial centroid is randomly sampled from a multivariate normal distribution, whereas with warm start the initial centroid is chosen as the closest image to the target from 100 randomly sampled images (this is similar to the "near task" in Ukkonen et al. [42]).

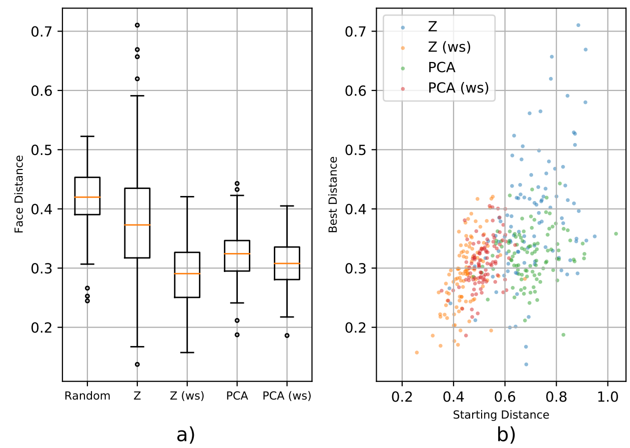

Figure 1: Rocchio performance on full image space: (a) distribution of distances from the best image found to the target image, (b) impact of initial centroid on final results. (Z = $\mathcal{Z}$-space, PCA = PCA-space, ws = warm start).

3.4.3 GP-UCB. In the experiments with GP-UCB, a single image was shown at each iteration on the basis of the upper confidence bound. We gave a reward equal to the negative distance between the current image and the target image. The search continues until an image close enough to the target is found or for a maximum of 400 iterations, i.e. the same image budget as Rocchio without warm start. In our experience, sampling from PCA-space was prone to producing unsatisfactory images when x is sampled too far from the origin. We therefore provided GP-UCB with the same bounds that result from Rocchio's use of a truncated normal distribution to constrain the search space.

3.4.4 Random Baseline. As an additional baseline, we randomly sampled 400 images from the search space, either $\mathcal{Z}$ or PCA-space, and find the closest image to the target image.

4 RESULTS

We investigated two experimental settings: (i) exploring the full GAN using either $\mathcal{Z}$ or PCA-space, and (ii) exploring a restricted space defined by the first n principal components in PCA-space. For each experimental setting, we performed 100 simulation runs using 100 randomly sampled target images. The same 100 target images were used to search the full GAN space using each method and a different 100 target images were generated for each number of principal components tested. This ensures that all targets are

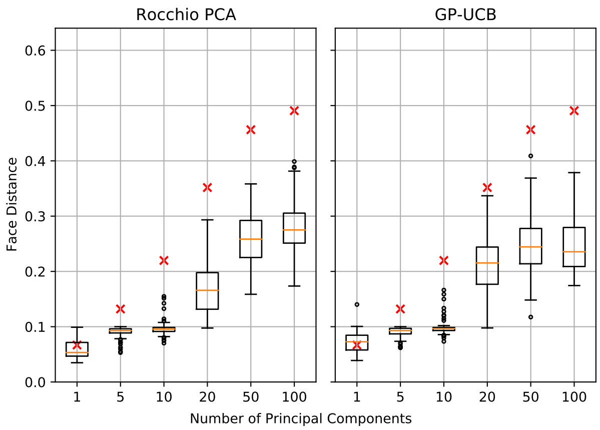

Figure 2: Distribution of distances from the best image found to the target image for different numbers of principal components for Rocchio (left) and GP-UCB (right). Red crosses are the median performance of random sampling.

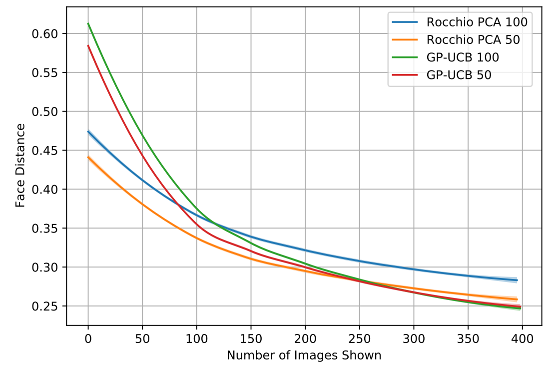

Figure 3: Time series of the average final distance to target image for Rocchio and GP-UCB searching 50 and 100 principal components.

reachable as an image that can be represented exactly in, for example, 20 principal components, can only be approximated in 10. In the PCA experiments, we used 1, 5, 10, 20, 50 and 100 principal components that explained 6.6%, 27.5%, 44.9%, 58.0%, 71.5% and 81.4% of the variance, respectively.

4.1 Full Image Space

Figure 1a shows the distribution of face distances between the target image and the best image found (lower distances are better). We simulated Rocchio in 512 dimensional $\mathcal{Z}$-space and in PCA-space using all 512 principal components, both with and without warm start. GP-UCB is absent from the plot as it was too computationally intensive to run on the full image space. For comparison, we also included the random baseline.

None of the simulation runs in Figure 1a managed to converge to the target image. In $\mathcal{Z}$-space, Rocchio benefited from warm start, improving the median face distance by 27.8% from 0.372 to 0.291. In PCA-space, however, warm start made less difference, only improving performance by 5.2% from 0.324 to 0.308. Rocchio did not perform as well as expected compared to simply sampling random images. Indeed, searching $\mathcal{Z}$-space without warm start frequently produced worse results than the median performance of random. Figure 1b shows how dependent Rocchio is on starting conditions: the lower the distance between the initial centroid and the target image, the better the final result (Pearson correlation of 0.45-0.55, depending on experimental setting).

4.2 Reduced Image Spaces

Figure 2 shows the distribution of face distances between the target image and the best image found (lower distances are better). We compared Rocchio with warm start and GP-UCB with different numbers of principal components ranging from 1–100. The red crosses show the median performance of random sampling.

For lower numbers of principal components, both methods performed similarly: converging in a majority of simulation runs for 1, 5 and 10 principal components. When searching more than 10 principal components, however, the performance of both methods degrades in terms of distance to target and overall spread. With 20 principal components, Rocchio outperformed GP-UCB by 29.8% in median distance to target. At the highest dimensionalities tested, GP-UCB outperformed Rocchio by 5.8% and 16.8% for 50 and 100 principal components, respectively. Figure 3 shows how the search progresses over time for 50 and 100 principal components. Despite GP-UCB having a significant disadvantage compared to Rocchio (GP-UCB does not use warm start), it catches up quickly and, in the case for 100 principal components, achieves similar distance to target at 250 images compared to Rocchio at 400 images.

5 SUMMARY

In this paper, we conducted a simulated study of GP-UCB and a variant of Rocchio's algorithm for performing exploratory search over a GAN. In our experiments, GP-UCB either tied with or exceeded the performance of Rocchio in 5/6 experimental settings (Figure 2), despite not benefiting from warm start. While GP-UCB appeared to scale better than Rocchio at higher dimensions (Figure 3), it was too computationally intensive to run on the full image space. Indeed, the best we managed to run was 100 principal components, covering 81.4% of explained variance of the full GAN image space.

Despite appearing to perform well, both methods only succeeded in converging with up to 10 principal components. We visually inspected the faces generated using 10 and 20 principal components, and noted that, despite only going from 44.9% to 58.0% explained variance, the variety of faces increased substantially in terms of more varied hair color, ethnicities and lighting conditions. This suggests that systems based on these approaches may struggle to satisfy users' information needs and more research is needed to understand how to search a dense continuous latent space within a constrained image budget.

ACKNOWLEDGMENTS

The authors wish to acknowledge CSC – IT Center for Science, Finland, for computational resources. This work has been supported by Helsinki Institute for Information Technology HIIT.

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