Generative Adversarial Active Learning

Jia-Jie Zhu
Computer Science Department, Boston College, Chestnut Hill, MA 02467-3859, USA

José Bento
Computer Science Department, Boston College, Chestnut Hill, MA 02467-3859, USA

Abstract

We propose a new active learning approach using Generative Adversarial Networks (GAN). Different from regular active learning, we adaptively synthesize training instances for querying to increase learning speed. Our approach outperforms random generation using GAN alone in active learning experiments. We demonstrate the effectiveness of the proposed algorithm in various datasets when compared to other algorithms. To the best of our knowledge, this is the first active learning work using GAN.

1. Introduction

One of the most exciting machine learning breakthroughs in recent years is the generative adversarial networks (GAN) (Goodfellow et al., 2014). It trains a generative model by finding the Nash Equilibrium of a two-player adversarial game. Its ability to generate samples in complex domains enables new possibilities for active learners to synthesize training samples on demand, rather than relying on choosing instances to query from a given pool.

In the classification setting, given a pool of unlabeled data samples and a fixed labeling budget, active learning algorithms typically choose training samples strategically from a pool to maximize the accuracy of trained classifiers. The goal of these algorithms is to reduce label complexity. Such approaches are called pool-based active learning. This pool-based active learning approach is illustrated in Figure 1 (a).

In a nutshell, we propose to use generative adversarial networks to synthesize informative training instances that are adapted to the current learner. We then ask human oracles to label these instances. The labeled data is added back to the training set to update the learner. This protocol is executed iteratively until the label budget is reached. This process is shown in Figure 1 (b).

The main contributions of this work are as follows:

- To the best of our knowledge, this is the first active learning work using deep generative models\(^1\). In fact, this is the first work to report satisfactory results in active learning synthesis for image classification (Settles, 2010; Lang and Baum, 1992). The proposed framework may lay the foundation for future GAN applications in active learning.

- Because we do not choose querying samples from the given pool, the performance of our active learner may not be upper-bounded by the that of fully supervised learning. With enough capacity from the trained generator, our method allows us to have control over the generated instances which may not be available to the previous active learners. While we do not claim our method is always superior to the previous active learners in terms of accuracy, in some cases, it yields classification performance not achievable even by a fully

\(^1\)The appendix of (Papernot et al.) mentioned three active learning attempts but did not report numerical results. Our approach is also different from those attempts.

\(x, y \rightarrow x, y \rightarrow x, y \rightarrow x, y\)

Figure 1. (a) Pool-based active learning scenario. The learner selects samples for querying from a given unlabeled pool. (b) GAAL algorithm. The learner synthesizes samples for querying using GAN.
supervised learning scheme.

- We conduct preliminary experiments to compare our active learning approach with self-taught learning. The results are promising.

2. Related work

Our work is related to two subjects, active learning and deep generative models.

Active learning algorithms can be categorized into stream-based, pool-based and learning by query synthesis. Historically, stream-based and pool-based are the two popular scenarios of active learning (Settles, 2010).

Our method falls into the category of query synthesis. Early active learning by queries synthesis achieves good results only in simple domains such as $X = \{0, 1\}^2$, see (Angluin, 1988; 2001). In (Lang and Baum, 1992), the authors synthesized learning queries and used human oracles to train a neural network for classifying handwritten characters. However, they reported poor results due to the images generated by the learner being sometimes unrecognizable to the human oracles. We will report results on similar tasks such as differentiating 5 versus 7, showing the advancement of our active learning scheme. Figure 2 compares image samples generated by the method in (Lang and Baum, 1992) and our algorithm.

![Figure 2](Image)

Our approach is also related to (Papernot et al., 2017) which studied GAN in semi-supervised setting. However, our task is active learning which is different from the semi-supervised learning they discussed. Our work share the common strength with the self-taught learning algorithm in (Raina et al., 2007) that both methods use the unlabeled data to help with the task. In Section 5.4, we compare our algorithm with a self-taught learning algorithm.

To the best of our knowledge, the only previous mentioning of using GAN for active learning is in the appendix of (Papernot et al.). The authors discussed therein three attempts to reduce the number of queries. In the third attempt, they generated synthetic samples and sorted them by the information content whereas we adaptively generate new queries by solving an optimization problem. There were no reported active learning numerical results in that work.

3. Background

We briefly introduce some important concepts in active learning and generative adversarial network.

3.1. Active Learning

In the PAC learning framework (Valiant and G., 1984), label complexity describes the number of labeled instances needed to find a hypothesis with error $\epsilon$. The label complexity of passive supervised learning, i.e. using all the labeled samples as training data, is $O\left(\frac{d}{\epsilon}\right)$ (Vapnik and Vapnik, 1998), where $d$ is the VC dimension of the hypothesis class $\mathcal{H}$. Active learning aims to reduce the label complexity by choosing the most informative instances for querying while attaining low error rate. For example, (Hanneke, 2007) proved that the active learning algorithm from (Cohn et al., 1994) has the label complexity bound $O(\theta d \log \frac{1}{\epsilon})$, where $\theta$ is defined therein as the disagreement coefficient, thus reducing the theoretical bound for the number of labeled instances needed from passive supervised learning. Theoretically speaking, the asymptotic accuracy of an active learning algorithm can not ex-
ceed that of an supervised learning algorithm. In practice, as we will demonstrate in the experiments, our algorithm may be able to achieve higher accuracy than the passive supervised learning in some cases.

Stream-based active learning makes decisions on whether to query the streamed-in instances or not. Typical methods include (Beygelzimer et al., 2008; Cohn et al., 1994; Dasgupta et al., 2007). In this work, we will focus on pool-based and query synthesis methods.

In pool-based active learning, the learner selects the unlabeled instances from an existing pool based on a certain criterion. Some pool-based algorithms make selections by using clustering techniques or maximizing a diversity criterion. Some pool-based algorithms make selections by using clustering techniques or maximizing a diversity criterion.

In the query synthesis scenario, an instance \( x \) is synthetized instead of being selected from an existing pool. Previous methods tend to work in simple low-dimensional domains (Angluin, 2001) but fail in more complicated domains such as images (Lang and Baum, 1992). Our approach aims to tackle this challenge.

For an introduction to active learning, readers are referred to (Settles, 2010; Dasgupta, 2011).

### 3.2. Generative Adversarial Networks

Generative adversarial networks (GAN) is a novel generative model invented by (Goodfellow et al., 2014). It can be viewed as the following two-player minimax game between the generator \( G \) and the discriminator \( D \),

\[
\min_{\theta_1} \max_{\theta_2} \left\{ \mathbb{E}_{x \sim p_{\text{data}}} \log D_{\theta_1}(x) + \mathbb{E}_{z \sim p_{\text{z}}} \log(1 - D_{\theta_2}(G_{\theta_2}(z))) \right\},
\]

where \( p_{\text{data}} \) is the underlying distribution of the real data and \( z \) is uniformly distributed random variable. \( D \) and \( G \) each has its own set of parameter \( \theta_1 \) and \( \theta_2 \). By solving this game, a generator \( G \) is obtained. In the ideal scenario, given random input \( z \), we have \( G(z) \sim p_{\text{data}} \). However, finding this Nash Equilibrium is a difficult problem in practice. There is no theoretical guarantee for finding the Nash Equilibrium due to the non-convexity of \( D \) and \( G \). A gradient descent type algorithm is typically used for solving this optimization problem.

A few variants of GAN have been proposed since (Goodfellow et al., 2014). The authors of (Radford et al., 2015) use GAN with deep convolutional neural network structures for applications in computer vision (DCGAN). DCGAN yields good results and is relatively stable. Conditional GAN (Gauthier, 2014; Dosovitskiy et al., 2014; Mirza and Osindero, 2014) is another variant of GAN in which the generator and discriminator can be conditioned on other variables, e.g., the labels of images. Such generators can be controlled to generate samples from a certain category. (Chen et al., 2016) proposed infoGAN which learns disentangled representations using unsupervised learning.

A few updated GAN models have been proposed. (Salimans et al., 2016) proposed a few improved techniques for training GAN. Another potentially important improvement of GAN, Wasserstein GAN, has been proposed by (Arjovsky et al., 2017). The authors proposed an alternative to training GAN which can avoid instabilities such as mode collapse with theoretical analysis. They also proposed a metric to evaluate the quality of the generation which may be useful for future GAN studies. Possible applications of Wasserstein GAN to our active learning framework are left for future work.

The invention of GAN triggered various novel applications. (Kadurin et al., 2016) applied adversarial autoencoder to drug discovery. (Yeh et al., 2016) performed image inpainting task using GAN. (Zhu et al., 2016) proposed iGAN to turn sketches into realistic images. (Ledig et al., 2016) applied GAN to single image super-resolution. Our study is the first GAN application in active learning.

For a comprehensive review of GAN, readers are referred to (Goodfellow et al., 2016).

### 4. Generative Adversarial Active Learning

In this section, we introduce our active learning approach which we call Generative Adversarial Active Learning.
Generative Adversarial Active Learning

(GAAL). It combines query synthesis with the uncertainty sampling principle.

The intuition of our approach is to generate instances which the current learner is uncertain about, i.e., applying the uncertainty sampling principle. To this end, we formulate the optimization problem

$$\min_z \left\{ L_{\text{active}}(G(z)) + L_{\text{reg}}(G(z)) \right\}, \quad (3)$$

where $z$ is the latent variable and $G$ is obtained by the GAN algorithm. The first term $L_{\text{active}}(G(z))$ is the loss function for generating an informative active learning query. A small value of $L_{\text{active}}(G(z))$ indicates the generated instance $G(z)$ is informative to the learner. The second term $L_{\text{reg}}(G(z))$ is a regularization term which ensures the quality of generated samples. In the aforementioned adversarial setting, it penalizes low-quality samples.

One particular choice for the loss function is based on uncertainty sampling of section 3.1. This specific adaptation of uncertainty sampling in this work may be better coined as uncertainty generation to indicate it is not a pool-based sampling scheme. In the setting of a classifier with the decision function $f(x) = W\phi(x) + b$, the (proxy) distance to the decision boundary is $\|W\phi(x) + b\|$. Similar to the intuition of (1), given a trained generator function $G$, we formulate the active learning synthesis as the following optimization problem

$$\min_z \left\{ \frac{1}{2}\|W^T\phi(G(z)) + b\|^2 + \lambda \log(1 - D(G(z))) \right\}, \quad (4)$$

where $z$ is the latent variable and $\lambda$ is a tunable parameter. Figure 3 (b) illustrates the intuition of GAAL. Compared with the pool-base active learning in Figure 3 (a), our hope is that it may be able to generate more informative instances than those available in the existing pool.

Figure 3. (a) SVM active algorithm selects the instances that are closest to the boundary to query the oracle. (b) GAAL algorithm synthesizes instances that are informative to the current learner. Synthesized instances may be more informative to the learner than other instances in the existing pool.

The solution(s) to this optimization problem, $G(z)$, after being labeled, will be used as new training data for the next iteration. We outline our procedure in Algorithm 1.

Algorithm 1 Generative Adversarial Active Learning (GAAL)

1. **Train generator $G$ on all unlabeled data by solving (2)**
2. **Initialize labeled training dataset $S$ by randomly picking a small fraction of the data to label**
3. **repeat**
   - **Solve optimization problem (4) according to the current learner by descending the gradient**
     $$\nabla_z \left\{ \frac{1}{2}\|W^T\phi(G(z)) + b\|^2 + \lambda \log(1 - D(G(z))) \right\}$$
   - **Use the solution $\{z_1, z_2, \ldots\}$ and $G$ to generate instances for querying**
   - **Label $\{G(z_1), G(z_2), \ldots\}$ by human oracles**
   - **Add labeled data to the training dataset $S$ and re-train the learner, update $W$, $b$**
4. **until** Labeling budget is reached

Formulation (3) offers the flexibility of using other loss terms. For examples, in the case of logistic regression as the classifier of choice, uncertain sampling principle in active learning corresponds to the active loss term choice $L_{\text{active}}(z) = -h(G(z)) \log h(G(z)) - (1 - h(G(z))) \log(1 - h(G(z)))$, where $h(x) = \frac{1}{1+e^{-x}}$ is the logistic function. $\theta$ is the parameter of the classifier, similar to $W$, $b$ in (4). The derivation of this formulation is analogous to the entropy measure in (Joshi et al., 2009).

It is also possible to use a state-of-the-art classifier, such as convolutional neural networks. To do this, we replace the feature map $\phi$ in Equation 4 with a feed-forward function of a convolutional neural network. In that case, the linear SVM will become the output layer of the network.

In training GAN, we follow the procedure detailed in (Radford et al., 2015). Optimization problem (4) is non-convex with possibly many local minima. One typically aims at finding good local minima rather than the global minimum. We use a gradient descent algorithm with momentum to solve this problem. We also periodically restart the gradient descent to find other solutions. The gradient of $D$ and $G$ is calculated using back-propagation.

Alternatively, we can maximize the diversity of the generated samples rather than relying on the uncertainty principle. Some active learning approaches rely on maximizing diversity measures, such as the Shannon Entropy. In our case, we can substitute the first term in the objective function (3) with a diversity measure such as proposed in (Yang et al., 2014; Hoi et al., 2009), thus maximizing the diversity. The evaluation of this alternative approach is left for future work.
5. Experiments

We perform active learning experiments in image classification on the MNIST, SVHN and CIFAR-10 datasets. We also compare our approach to self-taught learning, a type of transfer learning method. The GAN implementation used in our experiment is a modification of a publicly available TensorFlow DCGAN implementation\(^2\). The network architecture of DCGAN is described in (Radford et al., 2015).

In our experiments, we focus on binary classification. Although this can be generalized to multiple classes using one-vs-one or one-vs-all scheme (Joshi et al., 2009). We use a linear SVM as our classifier of choice, although we also tested logistic regression whose accuracy is slightly worse in most cases. Even though classifiers with much higher accuracy (e.g., convolutional neural networks) can be used, our purpose is not to achieve absolute high accuracy but to study the relative performance between different active learning schemes.

The following schemes are compared in our experiments.

- The proposed generative adversarial active learning (GAAL) algorithm as in Algorithm 1.
- Using regular GAN to generate training data. We refer to this as passive GAN.
- Tong&Koller’s SVM\_active algorithm from (Tong and Koller, 2002).
- Passive random sampling, which randomly samples instances from the unlabeled pool.
- Passive supervised learning, i.e., using all the samples in the pool to train the classifier.
- Self-taught learning from (Raina et al., 2007).

We initialize the training set with 50 randomly selected samples. The algorithms proceed with a batch of 10 new samples every time. In our experiments, six different human labelers participated in the labeling effort. Typical generated samples, which are presented to the labelers, are shown in Figure 4.

5.1. Handwritten Digits

The MNIST dataset is a well-known image classification dataset with 60000 training samples and 10000 test samples. The training set and the test set follow the same distribution. We perform the binary classification experiment distinguishing 5 and 7, as in (Lang and Baum, 1992). We use all the images of 5 and 7 from the MNIST training set as our unlabeled pool to train the generator G. Different from traditional active learning, we do not select new samples from the pool after the initial iteration. Instead, we apply Algorithm 1 to generate training query. For the generator D and G, we used a network structure similar to (Goodfellow et al., 2014; Radford et al., 2015; Salimans et al., 2016). We use linear SVM as our classifier although other classifiers can be used in active learning as well(Tong and Koller, 2002; Schein and Ungar, 2007; Settles, 2010). We test the trained classifier on a test set that follow a different distribution as the training set. The purpose is to demonstrate the adaptive capacity of the GAAL algorithm. To this end, we use the USPS dataset from (LeCun et al., 1989) as the test set with standard preprocessing. This test setting is related to the self-taught learning setting which we discuss in a later experiment.

Figure 5 shows the accuracy plot for the tested algorithms. When using the full training set, with 11000 training im-

\(^2\)https://github.com/carpedm20/DCGAN-tensorflow

Figure 4. Samples generated by GAAL. (Top) MNIST dataset. (Bottom) CIFAR-10 dataset.

Figure 5. Active learning results of the MNIST dataset, classifying 5 and 7. Results are averaged over 5 runs. Fully supervised learning accuracy is plotted as a horizontal line for comparison.
that level. It is close to the supervised accuracy with 250 training samples.

On the other hand, GAAL is able to achieve accuracy better than the fully supervised scheme. With 250 training samples, it achieves the accuracy of about 76.42%, which improves over supervised learning.

Obviously, the accuracy of both Tong&Koller and random sampling will eventually converge to the fully supervised learning accuracy.

Note that for the Tong&Koller algorithm, an exhaustive scan through the training pool is not always practical. In large datasets, one can employ the well-known trick of 59 (Smola and Schölkopf, 2000).

5.2. SVHN

The Street View House Numbers (SVHN) dataset contains over 600000 color 32 × 32 images of house numbers. Compared to the MNIST dataset, it is significantly more challenging due to its high dimensions. We perform active learning experiments on the SVHN dataset. Figure 6 shows the accuracy plot for this experiment.

Passive supervised learning achieves 56% accuracy using all the data in the pool, which is slightly better than random guesses. The GAAL method is able to achieve higher accuracy than fully supervised learning, again beating the random sampling and random GAN generation. Tong&Koller’s algorithm achieves similar accuracy as GAAL for up to 250 sample size. However, its accuracy will foreseeably drop towards the passive supervised learning as the training set size increases. The GAAL algorithm did not demonstrate as big of an improvement in this experiment as in the MNIST experiment. This may be due to the fact that the test and training sets follow the same distribution. This inspired us to later study the self-taught learning experiment.

In this dataset (as well as the CIFAR-10 dataset), our human labeler noticed significant higher chances of generation failure, e.g., instances fail to represent either of the categories. This may be because of the significantly higher dimensions than the MNIST dataset. We thus asked the labelers to only label the samples they can distinguish. We speculate recent improvements on GAN, e.g., (Salimans et al., 2016; Arjovsky et al., 2017), may help mitigate this issue. Addressing this limitation will be left to future studies.

5.3. CIFAR-10

The training set of CIFAR-10 dataset consists of 50000 32 × 32 color images from 10 categories. In the active learning setting, one might speculate the possibility of distinguishing cats and dogs by training on cat-like dogs or dog-like cats. In practice, our human labelers failed to confidently identify most of the generated cat and dog images. Figure 7 shows generated samples.

For this reason, we perform binary classification active learning on the automobile and horse categories. It is relatively easy for human labelers to identity car and horse body shapes. Figure 8 shows the results. In this experiment, GAAL performs on par with the random sampling scheme and better than the passive GAN scheme. However, it is not able to beat Tong&Koller’s active learning algorithm. This may be because that higher dimensions require more active learning iterations for GAAL to perform better. The authors of (Salimans et al., 2016) reported attempts to generate high-resolution animal pictures, but with the wrong anatomy. We leave this task for future studies, possibly with improved techniques such as (Arjovsky et al., 2017).

5.4. Comparison with Self-taught Learning

One common strength of GAAL and self-taught learning (Raina et al., 2007) is that both utilize the unlabeled data to help with the classification task. As we have seen in the MNIST experiment, our GAAL algorithm seems to be able to adapt to the learner. The results in this experiment are preliminary and not meant to be taken as comprehensive
Transfer learning concerns the case when the distribution of the training domain $P_{tr}(x, y)$ is different from that of the target domain $P_{te}(x, y)$. In our case, the training domain is mostly unlabeled. Thus the method we compare with is self-taught learning (Raina et al., 2007). Similar to the algorithm in (Le et al.), we use a Reconstruction Independent Component Analysis (RICA) model with a convolutional layer and a pooling layer. RICA is similar to a sparse autoencoder. Following standard self-taught learning procedures, we first train on the unlabeled pool dataset. Then we use trained RICA as the feature extractor to obtain higher level features from randomly selected MNIST images. We then concatenate the features with the original image data to train the classifier. Finally, we test the trained classifier on the USPS dataset. We test the training size of 250, 500, 1000, 2000 and 5000. The reason of doing so is that deep learning type techniques are known to thrive in the abundance of training data. They may perform relatively poorly with limited amount of training data, as in the active learning scenarios. We run the experiments for 100 times and average the results. We use the same setting for the GAAL algorithm as in Section 5.1. The classifier we use is a linear SVM. Table 1 shows the classification accuracies of GAAL, self-taught learning and baseline supervised learning on raw image data. Using GAAL on the raw features achieves a higher accuracy than that of the self-taught learning with the same training size of 250. In fact, self-taught learning performs worse than the regular supervised learning when labeled data is scarce. This is possible for an autoencoder type algorithm. However, when we increase the training size, the self-taught learning starts to perform better. With 5000 training samples, self-taught learning outperforms GAAL with 250 training samples.

Based on these results, we suspect that GAAL also has the potential to be used as a self-taught algorithm\(^3\). In practice, the GAAL algorithm can also be applied on top of the features extracted by a self-taught algorithm. A comprehensive comparison with a more advanced self-taught learning method with deeper architecture is beyond the scope of this work.

### 6. Discussion and Future Work

In this work, we proposed a new active learning approach that employs the Generative Adversarial Networks. While we do not claim our approach is always superior to traditional pool-based approach at this stage, our experiments show promising results.

The results of this work are enough to inspire future studies of deep generative models in active learning. However, work remains in establishing theoretical guarantees. The comparison of GAAL with self-taught learning is particularly interesting and worth further investigation. We also plan to investigate the possibility of using Wasserstein GAN in our framework, e.g., to address the issue mentioned in Section 5.2.

### References

D Angluin. Queries and concept learning. *Mach. Learn.*, 1988.

D Angluin. Queries revisited. *Int. Conf. Algorithmic
Generative Adversarial Active Learning

Learn., 2001.

Martin Arjovsky, Soumith Chintala, and Léon Bottou. Wasserstein GAN. jan 2017.

Alina Beygelzimer, Sanjoy Dasgupta, and John Langford. Importance Weighted Active Learning. Proc. 26th Annu. Int. Conf. Mach. Learn. ICML 09, abs/0812.4(ii):1–8, 2008. doi: 10.1145/1553374.1553381.

Antoine Bordes, eyda Ertekin, Jason Weston, and Léon Bottou. Fast Kernel Classifiers with Online and Active Learning. J. Mach. Learn. Res., 6:1579–1619, 2005. ISSN 1532-4435. doi: 10.1.1.60.9676.

Klaas Brinker. Incorporating Diversity in Active Learning with Support Vector Machines.

Colin Campbell, Nello Cristianini, and Alex Smola. Query learning with large margin classifiers. 17th Int. Conf. Mach. Learn., pages 111–118, 2000.

Xi Chen, Yan Duan, Rein Houthooft, John Schulman, Ilya Sutskever, and Pieter Abbeel. InfoGAN: Interpretable Representation Learning by Information Maximizing Generative Adversarial Nets. 2016.

Sanjoy Dasgupta, Two faces of active learning. Theor. Comput. Sci., 412:1767–1781, 2011. doi: 10.1016/j.tcs.2010.12.054.

Sanjoy Dasgupta and Daniel Hsu. Hierarchical sampling for active learning. Proceedings of the 25th international conference on Machine learning - ICML '08, pages 208–215, 2008. ISSN <null>. doi: 10.1145/1390156.1390183.

Sanjoy Dasgupta, Daniel Hsu, and Claire Monteleoni. A general agnostic active learning algorithm. Engineering, 20(2):1–14, 2007. doi: 10.1073/pnas.0703993104.

Alexey Dosovitskiy, Jost Tobias Springenberg, Maxim Tatschkenko, and Thomas Brox. Learning to Generate Chairs, Tables and Cars with Convolutional Networks. arXiv preprint arXiv:1411.5928, pages 1–14, 2014. ISSN 10636919. doi: 10.1109/CVPR.2015.7298761.

Jon Gauthier. Conditional generative adversarial nets for convolutional face generation. Class Project for Stanford CS231N: Convolutional Neural Networks for Visual Recognition, Winter semester 2014, 2014.

King-Shy Goh, Edward Y. Chang, and Wei-Cheng Lai. Multimodal concept-dependent active learning for image retrieval. In Proc. 12th Annu. ACM Int. Conf. Multimed. - Multimed. ’04, page 564, New York, New York, USA, 2004. ACM Press. ISBN 1581138938. doi: 10.1145/1027527.1027664.

Ian Goodfellow, Yoshua Bengio, and Aaron Courville. Deep Learning. MIT Press, 2016.

Ij Goodfellow, J Pouget-Abadie, and Mehdi Mirza. Generative Adversarial Networks. arXiv preprint arXiv: ..., pages 1–9, jun 2014. ISSN 10495258.

Steve Hanneke. A bound on the label complexity of agnostic active learning. Proc. 24th Int. Conf. Mach. Learn. - ICML ’07, pages 353–360, 2007. doi: 10.1145/1273496.1273541.

Steven C H Hoi, Rong Jin, Jianke Zhu, and Michael R Lyu. Semi-Supervised SVM Batch Mode Active Learning with Applications to Image Retrieval. ACM Trans. Informations Syst. ACM Trans. Inf. Syst. Publ. ACM Trans. Inf. Syst., 27(16):24–26, 2009.

Timothy M. Hospedales, Shaogang Gong, and Tao Xiang. Finding rare classes: Active learning with generative and discriminative models. IEEE Trans. Knowl. Data Eng., 25(2):374–386, 2013. ISSN 10414347. doi: 10.1109/TKDE.2011.231.

Prateek Jain, Sudheendra Vinoskar, Vijayanarasimhan, Kristen Grauman, Prateek Jain, and Kristen Grauman. Hashing Hyperplane Queries to Near Points with Applications to Large-Scale Active Learning. IEEE Trans. Pattern Anal. Mach. Intell., 36(2):2010, 2010. ISSN 01628828. doi: 10.1109/TPAMI.2013.121.

A.J. Joshi, F. Porikli, and N. Papanikolopoulos. Multiclass active learning for image classification. IEEE Conf. Comput. Vis. Pattern Recognit., pages 2372–2379, 2009. ISSN <null>. doi: 10.1109/CVPR.2009.5206627.

Artur Kadurin, Alexander Aliper, Andrey Kazennov, Polina Mamoshina, Quentin Vanhaelen, Kuzma Khrabrov, Alex Zhavoronkov, Artur Kadurin, Alexander Aliper, Andrey Kazennov, Polina Mamoshina, Quentin Vanhaelen, Kuzma Khrabrov, Alex Zhavoronkov, Artur Kadurin, Alexander Aliper, Andrey Kazennov, Polina Mamoshina, Quentin Vanhaelen, Kuzma Khrabrov, and Alex Zhavoronkov. The cornucopia of meaningful leads: Applying deep adversarial autoencoders for new molecule development in oncology. Oncotarget, 5(0), 2016. ISSN 1949-2553. doi: 10.18632/oncotarget.14073.

Kevin J. Lang and Eric B Baum. Query Learning Can Work Poorly when a Human Oracle is Used, 1992.
Quoc V Le, Alexandre Karpenko, Jiquan Ngiam, and Andrew Y Ng. ICA with Reconstruction Cost for Efficient Overcomplete Feature Learning.

Y. LeCun, B. Boser, J. S. Denker, D. Henderson, R. E. Howard, W. Hubbard, and L. D. Jackel. Backpropagation Applied to Handwritten Zip Code Recognition, 1989. ISSN 0899-7667.

Christian Ledig, Lucas Theis, Ferenc Huszar, Jose Caballero, Andrew Aitken, Alykhan Tejani, Johannes Totz, Zehan Wang, and Wenzhe Shi. Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network. arXiv, 2016.

Mehdi Mirza and Simon Osindero. Conditional Generative Adversarial Nets. CoRR, pages 1–7, nov 2014.

Hieu T Nguyen and Arnold Smeluders. Active Learning Using Pre-clustering.

Kamal Nigam, Andrew Kachites Mccallum, Sebastian Thrun, and Tom Mitchell. Text Classification from Labeled and Unlabeled Documents using EM. Mach. Learn., 39:103–134, 2000.

Nicolas Papernot, Martín Abadi, Ian Goodfellow, and Kunal Talwar. SEMI-SUPERVISED KNOWLEDGE TRANSFER FOR DEEP LEARNING FROM PRIVATE TRAINING DATA.

Alec Radford, Luke Metz, and Soumith Chintala. Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks. nov 2015.

Rajat Raina, Alexis Battle, Honglak Lee, Benjamin Packer, and Andrew Y Ng. Self-taught Learning : Transfer Learning from Unlabeled Data. Proc. 24th Int. Conf. Mach. Learn., pages 759–766, 2007. ISSN 1595937935. doi: 10.1145/1273496.1273592.

Tim Salimans, Ian Goodfellow, Wojciech Zaremba, Vicki Cheung, Alec Radford, and Xi Chen. Improved Techniques for Training GANs. jun 2016.

Andrew I. Schein and Lyle H. Ungar. Active learning for logistic regression: An evaluation, volume 68. 2007. ISBN 1099400750195. doi: 10.1007/s10994-007-5019-5.

Burr Settles. Active learning literature survey. Computer sciences technical report, 1648:University of Wisconsin–Madison, 2010. ISSN 00483931. doi: 10.1.1.167.4245.

AJ Smola and B Schölkopf. Sparse greedy matrix approximation for machine learning. 2000.