State-of-the-art performance and low system complexity has made deep-learning an increasingly attractive solution for big data analytics. However, limiting assumptions of end-to-end learning regimes hinder the use of neural networks on large application-grade datasets. This work addresses the assumption that output class-labels are defined for all classes in the domain. The amount of data collected by modern-day sensors span over an incomprehensible range of potential classes. Therefore, we propose a new learning regime where only some, but not all, classes of the training data are of interest to the classification system. The semi-supervised learning scenario in big data requires the assumption of a partial class mismatch between labelled and unlabelled training data. With classification systems required to classify source classes indicated by labelled samples while separating novel classes indicated by unlabelled samples, we find ourselves in an open-set case (vs closed set with only source classes). However, introducing samples from novel classes into the training set indicates a more relaxed open-set case. As such, our proposed regime of \textit{quasi-open set semi-supervised learning} is introduced. We propose a suitable method to train under quasi-open set semi-supervised learning that makes use of Wasserstein generative adversarial networks (WGANs). A trained classification certainty estimation within the discriminator (or critic) network is used to enable a reject option for the classifier. By placing a threshold on this certainty estimation, the reject option accepts classifications of source classes and rejects novel classes. Big data end-to-end training is promoted by developing models that recognize input samples do not necessarily belong to output labels. We believe this essential for big data analytics, and urge more work under quasi-open set semi-supervised learning.

\textbf{Keywords} Unknown classes · Novel classes · Source classes · Quasi-open set · Semi-supervised learning · Generative adversarial networks (GANs)

1 Introduction

End-to-end deep learning is at the forefront of the 4\textsuperscript{th} industrial revolution and, considering the low system complexity and computational cost required, is regularly argued to hold vast application potential \cite{25}. However, the development cost of neural network classifiers is prohibitive for large scale application grade datasets due to the nature of end-to-end, or input-output, training. Current end-to-end classification development processes (or learning regimes) require manually defining output labels for all classes in the studied domain. With modern sensors collecting vast amounts of data, this precondition is costly and impractical. Operative classification systems must, therefore, separate classes with defined labels (or source classes) from classes with undefined labels (or novel classes). Unfortunately, techniques to achieve this separation are restricted due to the characterization in the literature of novel classes removing them from the development stage. We, however, found that training under semi-supervised scenarios using large application-grade datasets indeed reveals novel classes during development. A new learning regime is, therefore, proposed that
With modern sensors collecting such vast amounts of unlabelled samples, we believe it reasonable to assume unlabelled samples, providing the system during the development/training phase with input samples, therefore, not of importance to this discussion. Have been manually gathered for certain source classes, a semi-supervised scenario with a vast number of unlabelled training samples from all classes in the domain are available during training. Given that labelled training samples are assumed to come from the same set of source classes as the labelled training samples \([22]\). In this work, we instead assume a so-called partial class mismatch between labelled and unlabelled training samples. In other words, unlabelled samples from novel classes into the training phase. The inclusion of unlabelled novel class samples during training alleviates open-set complications as suitable classification boundaries can be learnt according to novel classes. As such, two well-known learning regimes are identified:  

- The simplest, most popular, learning regime named fully supervised learning defines all samples seen during the training phase as input-output labelled pairs. Supervised systems are tasked to directly learn input-output transformations \((S_{(trn)}^{(lm)} \rightarrow L_{(trn)}^{(lm)} \in L^{(mn)})\) for all training samples \([9]\).
- Semi-supervised learning is a relaxed case of fully supervised learning as it has some labels of training samples unobserved as training sets consists of both labelled and unlabelled samples \([10]\). Although explicit definitions of which classes unlabelled samples belong to are not provided, including them in the training phase aids in the learning process.

For both regimes, source class-labels in \(L\) are defined according to labelled training samples. A more complex and general situation arises when input samples belong to novel classes that do not have defined labels in \(L\). This can be ignored in certain non-sensitive applications resulting in classifications of samples from novel classes into source class-labels. However, in more sensitive applications such as medical diagnosis or self-driving cars, classifiers must avoid making incorrect classifications. Models must rather classify novel classes as unknown than incorrectly classify them. The task of training classification systems to separate novel classes into an “unknown” class-label while also classifying source classes into their respective class-labels has become crucial and evermore widely studied under open-set recognition \([35]\). After training, the testing phase acts as a way to independently verify trained models’ accuracy scores\(^1\). Under open-set recognition, models are tested on samples that belong to both source classes seen during training and novel classes not seen during training. Therefore, the system has no means of defining class-labels for novel classes. As a result of not having any training samples available for novel classes, the general principle for achieving open-set recognition is to place classification boundaries around source classes with any sample falling outside this boundary deemed from a novel class \([29]\). The difficulty arises when deciding the distance of such classification boundaries as it cannot be inferred according to outside classes. We argue a more appropriate solution would be to relax the open-set case to allow unlabelled samples from novel classes into the training phase. The inclusion of unlabelled novel class samples during training alleviates open-set complications as suitable classification boundaries can be learnt according to novel classes.

Semi-supervised learning contains training samples both with and without labels. In general, unlabelled training samples are assumed to come from the same set of source classes as the labelled training samples \([22]\). In this work, we instead assume a so-called partial class mismatch between labelled and unlabelled training samples. In other words, unlabelled training samples might belong to either source or novel classes. As such, we find ourselves in a relaxed setting of open-set recognition, where novel classes with undefined labels are encountered during the training phase. As such, our new learning regime of quasi-open set semi-supervised learning is introduced. Within quasi-open set semi-supervised learning models are trained with labelled samples that define source class-labels and unlabelled samples which could or could not belong to those classes with defined labels. Models must be trained to classify source classes while also being aware that samples may be encountered that belong to classes outside those that the system is aware of. Under quasi-open set semi-supervised learning, the separation of novel classes from source classes, in principle, should be somewhat easier than general open-set recognition as the training is exposed to samples from both source and novel classes.

With modern sensors collecting such vast amounts of unlabelled samples, we believe it reasonable to assume unlabelled training samples from all classes in the domain are available during training. Given that labelled training samples have been manually gathered for certain source classes, a semi-supervised scenario with a vast number of unlabelled samples, \(S\), with their required outputs, \(L\), explicitly defines the respective outputs or source class-labels. Depending on the learning regime used, training input samples do not all require output class-labels. As such, two well-known learning regimes are identified:  

1. Unsupervised learning does not concern itself with labels as systems only determine how similar samples are to each other. It is, therefore, not of importance to this discussion.
2. The hyper-parameter tuning validation phase is not important for this discussion.
training samples would recognize labelled training samples representing classes of interest to the application (source classes), while unlabelled training samples represent the entire class domain, even classes not of interest (source and novel classes). Under such a quasi-open set semi-supervised setting, operational classifiers must achieve separation of classes of interest from those not of interest. As such, we hold it fundamental for the future of classifier development for large application-grade domains to train under quasi-open set semi-supervised learning. For further clarification, we use an example application of crop-classification using pixel-wise hyperspectral satellite images.

The Indiana Pines hyperspectral satellite image dataset \cite{2} has been regularly used within research to test the validity of crop-classification at a pixel-level of such images \cite{8,26,14,34}. The situation is summarized as follows:

- We are interested in developing a system to classify pixel-samples of a hyperspectral satellite image into one of 17 crop classes.
- For training, an image is available consisting of a small number of labelled pixel samples (into these 17 source classes) and a large number of unlabelled pixel samples.
- With satellite images spanning over many classes besides the required crop source classes, unlabelled pixel samples must be assumed to either belong to a source or novel class. However, by nature of unlabelled samples, it is impossible to distinguish whether an unlabelled sample is from a source or novel class.
- An operative classifier would encounter all class types in the satellite image domain. Separation of novel classes must be realized to make classification of source classes useful.
- For this scenario, training under quasi-open set semi-supervised learning is not only enforced by the semi-supervised criteria of the training data but also necessary to ensure fully-operational classifiers are developed.

Within this work, after describing the uniqueness of our new learning regime, the first method for training under quasi-open set semi-supervised learning is proposed. Our method exploits the unsupervised learning proficiency of generative adversarial networks (GANs) and recent advancements in semi-supervised learning using GANs to achieve quasi-open set semi-supervised learning. Specifically, Wasserstein GAN (WGANs \cite{4} are used due to their stable training under low complexity architectures and no hyper-parameter tuning. Quasi-open set semi-supervised learning is then achieved by training a reject option within the discriminator (also known as the critic) network which also acts as the classifier itself. The reject option then rejects the classification of samples from novel classes and accepts the classification of source classes.

Experiments for our proposed method are first conducted on the MNIST dataset, which contains ten digit classes. Our training sets consist of sparsely labelled training samples for seven classes and abundant unlabelled training samples for all ten classes. Therefore, class-labels are defined for seven source classes and undefined for the extraneous three novel classes. Results, with simple fully-connected network architectures and no hyper-parameter tuning, show near-perfect rejection of samples from novel classes (upwards of 97%), and high classification accuracy scores for source classes. However, this comes at the cost of also rejecting some samples from source classes. A more complex experiment is then conducted on a combined dataset of MNIST and Fashion-MNIST (a similar dataset to MNIST, yet containing different clothing classes). The training set consists of sparsely labelled training samples for MNIST source classes and abundant unlabelled training samples for both MNIST source classes and Fashion-MNIST novel classes. Again, near-perfect rejection of novel classes is achieved, coming at the cost of rejecting some samples from source classes.

Within this study, quasi-open set semi-supervised learning is introduced as a more appropriate learning regime for end-to-end classifier development using large application-grade datasets. A literature study is provided to describe the uniqueness of this new learning regime, after which the first method for training under this regime is proposed. Experimental results are promising, and so we hold this a suitable introductory method to quasi-open set semi-supervised learning. It is believed fundamental for operation classifier development to train under quasi-open set semi-supervised learning, and so we urge more work to train under this regime.

2 Background

Several learning regimes and research fields are identified to note the uniqueness of quasi-open set semi-supervised learning. Characterization of novel classes differ between each, yet the overlying principle that novel classes are unknown to the classification system remains the same.

- Zero-shot learning aims at developing systems that detect individual novel classes (or target classes as referred to in the literature) with zero training samples from the novel class. Zero-shot learners are tasked to define class-labels for novel classes with respect to the source class output scores of an already trained classifier. This by using available semantic information about each novel class \cite{23} \cite{24}.
Zero-shot learning has also been extended to a semi-supervised framework by introducing unlabelled samples from novel classes during training [19].

- One-shot learning [17] and its extension of few-shot learning [30] similarly aims to define class-labels for novel classes using a trained classifier on source classes. Different from zero-shot learning, one or a few training samples are available for the studied novel class. One-shot and few-shot learning has also been extended to semi-supervised learning by introducing unlabelled training samples from novel classes in conjunction with their one or few labelled training samples [6].
- One-class classification is the research field that tasks models to differentiate between one source class, for which training samples are available, and many novel classes, for which no training samples are available. Binary classification is, therefore, applied into either the source class or the blanket "unknown" class representing all novel classes [15, 27]. One-class semi-supervised learning again introduces unlabelled training samples from novel classes [18, 20, 5].

Quasi-open set semi-supervised learning trains models to separate novel classes from source classes while still classifying multiple source classes. Novel classes are not, such as in zero-shot/one-shot/few-shot learning, individually identified through new label definitions but instead enveloped in the blanket "unknown" class similar to one-class classification. Dissimilar to one-class classification where a single class is identified out of the entire domain, quasi-open set semi-supervised learning defines multiple source class-labels with an unknown number of novel classes.

3 Proposed method

Our proposed method for quasi-open set semi-supervised learning combines semi-supervised learning methods using GANs with the principles of classification with a reject option. In the following, we discuss general semi-supervised learning (i.e. no novel classes) using GANs including the application thereof on WGANs. Furthermore, we extend this discussion to our novel approach for training a reject option within the same network as the classifier.

3.1 Generative adversarial networks

The original GAN (or vanilla GAN [11]) consists of two fully-connected adversarial neural networks playing a min-max game. Of optimal convergence known as Nash equilibrium is reached, the generator network ($G$) is capable of transforming random noise vectors $z \sim \mathbb{P}(z)$ into fake samples ($G(z)$) similar to those in the training set. $\mathbb{P}(z)$ is simply a random normal distribution. The discriminator network ($D$) is tasked to output a score between 0.0 and 1.0 with fake generated samples ($D(G(z))$) having a score closer to 0.0 and real training samples ($D(x)$, with $x \sim \mathbb{P}(x)$ and $\mathbb{P}(0)$ the training distribution) a score closer to 1.0. The generator attempts to fool the discriminator by generating fake samples so realistic that they are deemed real by the discriminator. Theoretically, at Nash equilibrium the generated samples are so realistic that the discriminator outputs a score of 0.5 for both real and fake samples indicating complete uncertainty. This game between the generator and discriminator is described through a min-max game which is given by:

$$\min_{G} \max_{D} \quad \mathbb{E}_{x \sim \mathbb{P}(x)} \left[ \log(D(x)) \right] - \mathbb{E}_{z \sim \mathbb{P}(z)} \left[ \log(1 - D(G(z))) \right]$$

GANs are unsupervised learning methods as models are required to learn the differences and similarities of training set samples to ensure generated samples have these same characteristics. For well-converged GANs, learnt class discrepancies are evident as generated samples belong to discrete training domain classes. The adversarial game also suggests that the discriminator networks hold class knowledge, which is substantiated by their ability of achieving high accuracy semi-supervised learning. Semi-supervised learning within discriminator networks is accomplished by applying a supervised loss function on the discriminator in conjunction with the min-max game [21]. Although semi-supervised GAN methods do not hold state-of-the-art results [33], the end-to-end training and low system complexity makes it an attractive semi-supervised solution.

Under semi-supervised learning, sparsely labelled training samples define source class-labels for the classification system. Under a GAN framework, the discriminator’s classification task requires a binary label element for real and fake samples. With neural network classification generally making use of one-hot encoded labels [3], a typical solution for source class-labels and real/fake GAN class-labels at the discriminator’s output is to apply one-hot encoding over $K + 1$ discriminator output nodes (with $K$ the number of source class-labels). To achieve such a label framework, the real/fake samples score is first swapped around by swapping signs of the min-max game in eq. 1 (i.e. real samples have a low score 0.0 and fake samples a high score 1.0). The real/fake GAN label and the source class-labels can then
be defined under the same one-hot encoded labelling framework, with real samples having a high one-hot encoded label at one of \( K \) nodes, and fake samples a high one-hot encoded label at the \( K + 1 \)th node. As such, both the class labels over \( K \) nodes and the real/fake sample score at the \( K + 1 \)th node are adhered to. This \( K + 1 \) layout was the first developed method for training GANs for semi-supervised learning (SGAN \[21\]). However, the previously mentioned Nash equilibrium results in discriminators producing output scores of 0.5 for real and fake samples at the \( K + 1 \)th node. Classification accuracy scores are therefore suppressed, as real samples are classified as fake.

Salimans et al. in \[28\] recognized a different layout which has since been used for all state-of-the-art semi-supervised GAN methods. \[16\] \[17\] \[22\]. They stated that the above described \( K + 1 \) discriminator output layout results in over-parameterization of an applied softmax output activation function. Therefore, it is reasoned that a more appropriate layout is that of only \( K \) nodes at the discriminator’s output with the real samples defined as having all \( K \) nodes sum to one (allowing general one-hot encoded classification across \( K \) nodes), while fake samples has all \( K \) nodes sum to zero. Although this \( K \) layout has produced superior results, the training loss function used to accomplish this real/fake framework unnecessarily increases the complexity of the system (see eq. 5 from \[16\]). A more suitable scheme is, therefore, introduced which makes use of Wasserstein GANs (WGANs).

### 3.1.1 Wasserstein GANs for semi-supervised learning

WGANs are a specific type of GAN that minimize the Earth Mover’s probability density distance (EMD) \[31\] between the densities of real and generated data instead of the Kullback-Leibler distance (KLD) as in vanilla GANs. Minimizing the EMD has shown to both improve stability of training and produce high-quality results using far less complex architectures and no hyper-parameter tuning \[4\]. The derivation of the EM distance in \[4\] enforced a Lipschitz continuity constraint on both the discriminator (also called the critic in WGANs) and generator network. However, full Lipschitz continuity has not yet been enforced within any WGAN work, hindering its use on more complex architectures. In this work, we use the WGAN with gradient penalty (WGAN-GP), which partially enforces Lipschitz continuity allowing for more stable training.

The derived min-max game of WGANs is given as:

\[
\min_G \max_D \mathbb{E}_{x \sim P_{\text{data}}} [D(x)] - \mathbb{E}_{z \sim P_{\text{noise}}} [D(G(z))] \tag{2}
\]

Simply put, the WGAN min-max game tasks the critic to maximize its output for real samples and minimize it for fake samples. The generator, similar to vanilla GANs, initiates an adversarial game as it attempts to maximize the critic’s output given fake samples. This real/fake task of WGANs is similar to that of vanilla GANs, with the only difference that outputs aren’t constrained between 0 and 1.0.

The WGAN loss functions from eq. 2 minimizes and maximizes the vector output of the critic network. A vector loss function allows defining the critic output to any size without having to change eq. 2. The critic’s output is, therefore, defined to \( K \) output nodes to realize \( K \) source class-labels. Consequently, the framework of fake samples is minimized and real samples are maximized is synonymous to the \( K \) layout described above (real sums to one and fake sums to zero) except that the output isn’t bounded between 0.0 and 1.0. Semi-supervised learning can then be accomplished by simply appending a general supervised loss function for a one-hot encoded label framework to the WGAN min-max game. Also appending the gradient penalty from WGANs-GP \[12\] to ensure partial enforcement of the Lipschitz continuity, a total semi-supervised learning WGAN-GP min-max game is given as:

\[
\min_G \max_D \mathbb{E}_{x \sim P_{\text{data}}} [D(x)] - \mathbb{E}_{z \sim P_{\text{noise}}} [D(G(z))] - \lambda \mathbb{E}_{x \sim P_{\text{data}}} \left[ \left( \| \nabla_x D(x) \|_2 - 1 \right)^2 \right] + \mathbb{E}_{x, y \sim P_{\text{data}}} \left[ \sum_{k=0}^{K} y_k \log(D^k(x)) \right] \tag{3}
\]

With \( D^k \) being the discriminator’s output at node \( k \) after a softmax activation function is applied over all \( K \) output nodes. \( \lambda \) is the gradient penalty coefficient and is set to \( \lambda = 10 \) in all experiments as in the WGAN-GP paper. Furthermore, \( P_{\text{data}} \) is a combined set of real and generated samples. For the supervised loss, \( P_{\text{data}} \) is the set of all labelled training samples while \( y_k \) is a labelled sample’s one-hot encoded label at position \( k \) (either a 0 or a 1). A TensorFlow code snippet of this min-max game is shown in Appendix A. We leave thorough evaluation of this general semi-supervised framework for future work as Lipschitz continuity must first be fully realized within the networks to allow fair comparison to other works. Preliminary experiments on MNIST are conducted under very simple fully-connected architectures and no hyper-parameter tuning.

Experimental setup (architecture, learning rate, batch size, noise vector size) is shown in Appendix B. An average test accuracy score of \( \pm 96.11\% \) is achieved with a training set consisting of 200 labelled samples per class and 5000 unlabelled samples per class. Semi-supervised learning using WGANs-GP is clearly a viable option as respectfully high accuracy scores are achieved using simple experimental conditions. Considering the low system complexity of this framework, we believe that further work is undoubtedly warranted. As to return to quasi-open set semi-supervised
learning, this semi-supervised learning using WGAN-GP framework is used and expanded on to train a reject option in conjunction with the classifier in the critic network.

3.2 Classification with a reject Option

Reject options are used in conjunction with classifiers to only accept classification results that have high enough confidence or certainty of being correct. Classifications with too much uncertainty are rejected, as to say the system withholds predicting a label for rejected samples [13]. With general neural network softmax classification systems notorious for incorrectly classifying samples with high degrees of certainty [1], we opt to explicitly train a certainty estimation via end-to-end means. This trained certainty estimation is then used to enable the reject option.

Training sets within quasi-open set semi-supervised learning consist of labelled samples and unlabelled samples. The nature of an unlabelled sample translates to systems being uncertain which classes they belong to, be they from source or novel classes. Moreover, labelled samples have systems certain which source classes they belong to. This systems certainty relative to the training data is trained as a binary classification problem with labelled training samples \( \mathbb{P}(\text{lab}) \) producing output scores close to 0.0 and unlabelled training samples \( \mathbb{P}(\text{unlab}) \) producing output scores close to 1.0. Under quasi-open set semi-supervised learning, the required end result of the certainty measurement is the separation of source and novel classes via the reject option. Due to the \( \mathbb{P}(\text{unlab}) \) containing samples from both source and novel classes, independently training this binary classification won’t accomplish an effective certainty estimation. However, we found that cooperatively training a semi-supervised classification criteria with this binary classification does realize an effective certainty measurement.

The WGAN-GP semi-supervised framework, outlined by eq. 3, is extended to contain an extra output node to represent the certainty estimation. At this extra node, we train the binary classification problem described. Furthermore, the supervised criterion in eq. 3 is extended across \( K + 1 \) output nodes. This requires extending the one-hot encoded labelling system to \( K + 1 \) elements which is already enabled through the binary classification criterion for the \( K + 1 \)th node described above. In other words, samples from source classes will have a high one-hot encoded label at one of \( K \) nodes and, therefore, should have a low at the \( K + 1 \)th node. This coincides with binary classification problem where high certainty (as required for source classes) is trained as 0.0 at the \( K + 1 \)th node. Consequently, combining the classification over \( K \) nodes with the certainty at the \( K + 1 \)th node under the same softmax activation function realizes a classification system with a reject option enabled by the certainty measurement. As such, the entire loss function is described by the following min-max game:

\[
\min_{G} \max_{D} \quad \mathbb{E}_{x \sim \mathbb{P}(\text{unlab})} \left[ D(x) \right] - \mathbb{E}_{z \sim \mathbb{P}(\text{z})} \left[ D(G(z)) \right] - \lambda \mathbb{E}_{x \sim \mathbb{P}(\text{lab})} \left[ \| \nabla_x D(x) \|_2 - 1 \right]^2 + \mathbb{E}_{x, y \sim \mathbb{P}(\text{unlab})} \left[ \sum_{k=0}^{K+1} y_k \log(D^K(x)) \right] - \mathbb{E}_{x \sim \mathbb{P}(\text{unlab})} \left[ \log(D^{K+1}(x)) \right] - \mathbb{E}_{x \sim \mathbb{P}(\text{unlab})} \left[ \log(1 - D^{K+1}(x)) \right]
\]

(4)

Appendix B shows a TensorFlow code snippet of this total loss function. With a classifier and reject option coinciding under the same softmax, a unique inference scheme is required. Given a reject option threshold \( \gamma \) for the acceptance and rejection of classifications, our inference scheme is summarized through the following algorithm.

4 Experimental setup

Two conducted experiments are discussed – one with the introductory MNIST digit data-set and the other with a data-set of MNIST and Fashion-MNIST combined. For both experiments, source classes are defined by providing labelled and unlabelled training samples for these classes. Furthermore, novel classes are introduced by only providing unlabelled training samples for set novel classes. Model performance is measured through the rejection ratios for both source and novel classes. Additionally, testing the general semi-supervised learning using WGAN-GP framework, as described by eq. 3. Afterwards, our proposed method is used. For both frameworks, the effect of the number of labelled training samples is tested by providing 0, 50, 100, 200 and 400 labelled samples per source class. In the set of unlabelled training samples, we balanced the number of source and novel instances to 5000 of each.
Algorithm 1 Inference of classification with reject option given the training set $P^{(trn)}$, the test set $P^{(tst)}$ whose samples are inferred, the critic’s output after a softmax activation function ($D^0, D^1, D^2, \ldots, D^{K-1}, D^K, D^{K+1}$), and the reject option threshold $\gamma$

1: max = 0
2: min = 1
3: for each training sample $S$ in $P^{(trn)}$ do
4: Output at reject node $= D^{K+1}(S)$
5: if $D^{K+1}(S) >$ max then
6: max $= D^{K+1}(S)$
7: end if
8: if $D^{K+1}(S) <$ min then
9: min $= D^{K+1}(S)$
10: end if
11: end for
12: for each test sample $S$ in $P^{(tst)}$ do
13: Output at reject node for inferring sample $= D^{K+1}(S)$
14: Normalized $= (D^{K+1}(x) - \text{min})/(\text{max} - \text{min})$
15: if Normalized $< \gamma$ then
16: Classification of $x = \text{argmax}(D^0(S), D^1(S), D^2(S), \ldots, D^{K-1}(S), D^K(S))$
17: end if
18: if Normalized $\geq \gamma$ then
19: Classification of $x$ = Unknown
20: end if
21: end for
22: end for

In the second experiment we combined the MNIST and Fashion-MNIST data sets. These data-sets are compatible in that they both have white-coloured images with a black background of size 28 x 28. Their images, however, differ markedly with MNIST containing digit classes, and Fashion-MNIST clothing classes. This setting tests whether our proposed method will appropriately handle a situation where source and novel classes are from different domains. Therefore, the MNIST classes are all defined as source classes while the Fashion-MNIST classes are all defined as novel classes. The architectures and learning rate for this experiment is indicated in Appendix C. The training set consists of 100 labelled training samples for MNIST source classes and 5000 unlabelled training samples for all MNIST source classes and Fashion-MNIST novel classes.

For the performance of quasi-open set semi-supervised learning we introduce a confusion matrix variant indicated by Fig. 1. Rows are defined for all source classes with respective columns for the classifier predictions of their respective labels (similar to a general confusion matrix). Dissimilar to general confusion matrices, an extra row is defined for all novel classes and an extra column for all rejected samples. These confusion matrices and several counts indicated by them will be used for experimental analysis. Namely the following counts are used:

1. The number of non-rejected samples from source classes correctly classified into their respective labels.
2. The number of rejected samples from source classes.
3. The number of rejected samples from novel classes.

All counts are expressed as accuracy percentages over the total number of samples relative to that category. For our proposed method, the trend of these percentages will be shown in experimental analysis over various $\gamma$ values ranging from (0.05, 0.95). All results are test set accuracy scores averaged over 10 runs, each run having different data-set shuffling and initialization seeds.

5 Results

5.1 MNIST

General semi-supervised learning using WGANs-GP with various numbers of labelled training samples are first conducted. Confusion matrices for single runs are shown in Fig. 2. Over 10 separate runs, the average accuracy scores for 50 labels per class is 96.4%, 100 labels per class is 97.6%, 200 labels per class is 98% and 400 labels per class
98.3%. As expected, the classification accuracy for source classes increase the more labelled training samples for these classes are available. Also as expected, the rejection of novel classes is 0% for all experiments as novel classes are classified into source class-labels. These results show the need to train under quasi-open set semi-supervised learning to appropriately handle novel classes.

We then conducted the same experiments using our proposed method with a reject option. Fig. 3 shows the results averaged over 10 runs, with rejection threshold gamma varied from 0.05 to 0.96. For a small number of labelled training samples (50 from Fig. 3a and 100 from Fig. 3b), a high accuracy, upwards of 97%, is seen for successful rejection of
novel classes over the entire $\gamma$ spectrum. This is clearly at the cost of rejecting a large percentage of the source samples. The accuracy for non-rejected samples from classes with defined labels remains high across the entire $\gamma$ spectrum above 98% which is similar when increasing the number of labelled training samples (200 from Fig. 3c and 400 from Fig. 3d). Increasing the number of labelled training samples also drastically decrease the number of samples rejected from source classes. This is clearly at the cost of rejecting novel samples as seen most prominently under the 400 labelled training samples experiment. We find this result counter-intuitive as one would expect an increase in source class knowledge would result in better distinction between source and novel classes. We believe the cause for this is an imbalance of the number of training samples from source and novel classes.

![Graphs showing MNIST test results for different number of labelled training samples per source class and 5000 unlabelled training samples for all classes using our proposed method.]

**MNIST combined with Fashion-MNIST**
Results of the combined data-set experiment of MNIST and Fashion-MNIST averaged over 10 runs is also shown as a graph over the $\gamma$ spectrum in Fig. 4. Our proposed method successfully rejects novel classes with near-perfect test accuracy scores upwards of 99%, yet this is, again, at the cost of rejecting samples from source classes. Therefore, this experiment indicates the same cost as the MNIST experiment above yet it shows our proposed method successfully translates to more complex scenarios containing source and novel classes from different domains.

From these experiments, it is clear that our proposed method holds promise for quasi-open set semi-supervised learning, especially when considering the low system complexity. Further work is required to test the proposed method under more rigorous settings (such as differently balanced sets). The separation of novel classes with high classification accuracy of non-rejected source classes indicates a successful introductory method for quasi-open set semi-supervised learning.
Figure 4: MNIST combined with Fashion-MNIST test results with 100 labelled training samples per MNIST class and 5000 unlabelled training samples per class for all MNIST and Fashion-MNIST classes

6 Conclusion

In this work, the new learning regime of quasi-open set semi-supervised learning is introduced. Under this regime labelled training samples belong to source classes while unlabelled training samples belong to both source and novel classes. As a result of only being encountered as unlabelled samples, novel classes do not have defined class-labels. This calls for new training framework that is able to automatically separate novel classes from source classes. We argue that inserting unlabelled novel classes into the training phase provides an easier training setting to recognize novel class separation compared to open set recognition. Furthermore, we found this regime holds more true to large-scale application-grade datasets. Further work under quasi-open set semi-supervised learning is therefore encouraged.

An introductory method to quasi-open set semi-supervised learning was proposed. Specifically, we extended the semi-supervised learning framework using GANs to WGANs-GP due to their stable training. Further extension of this framework to contain a reject option concerning uncertain classifications was described. Such a reject option is tasked to accept the classification of source samples while rejecting the classification of novel samples. Our proposed method showed high accuracy for the rejection of novel classes and classification of source classes. This was, however, at the cost of rejecting the classifications of source classes. It was also found that accuracy for rejecting novel classes dropped when the number of labelled training samples increased. Further work is required to address this inconsistency, while we believe balancing of datasets to be a possible solution. As such, we hold that our proposed method acts as a suitable introductory method to quasi-open set semi-supervised learning.
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[35] Ryota Yoshihashi et al. Classification-Reconstruction Learning for Open-Set Recognition. 2019, pp. 4016–4025.
A Code snippet of semi-supervised learning using WGAN-GP loss functions

```python
self.x = tf.placeholder(tf.float32, [None, self.noise_dim, name='x])
self.real_image_pl = tf.placeholder(tf.float32, [None, self.dataset.img_size, self.dataset.img_size, self.dataset.channels], name='real_image_pl')
self.real_image_pl_2 = tf.placeholder(tf.float32, [None, self.dataset.img_size, self.dataset.img_size, self.dataset.channels], name='real_image_pl_2')
self.sgt_labels_pl = tf.placeholder(tf.float32, [None, self.dataset.num_classes + 1], name='sgt_labels_pl')
self.x_noise = self.generator(self.x)
self.real_dist = self.discriminator(self.real_image_pl, reuse=True)
self.d_fake = self.discriminator(self.x_noise, reuse=True)
self.g_fake = self.discriminator(self.x_noise, reuse=True)

# wgan loss
self.d_loss = tf.reduce_mean(tf.nn.relu(tf.reduce_mean(self.d_fake) - tf.reduce_mean(self.d_real)) + self.g_loss)
self.d_loss = tf.reduce_mean(self.d_fake - self.d_real)

# model supervision loss
self.d_loss_sup = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(labels=self.sgt_labels_pl, logits=self.g_fake) + self.g_loss)

# wgan gradient penalty loss
with tf.name_scope('gradient_penalty'):
    d_grad = tf.gradients(tf.reduce_mean(d_temp), d_temp)[0]
    grad_penalty = tf.reduce_mean(tf.squared_difference(d_grad, tf.zeros([d_grad.get_shape()])))
    grad_penalty = tf.reduce_mean(tf.squared_difference(d_grad, tf.zeros([d_grad.get_shape()])))
    grad_penalty = tf.reduce_mean(tf.squared_difference(d_grad, tf.zeros([d_grad.get_shape()])))
self.d_loss_sup = self.d_loss_sup + grad_penalty

Figure 5: TensorFlow code snippet of total loss given by eq 4 within a WGAN class
```
A WGAN-GP semi-supervised learning preliminary test

MNIST images are originally size 28 x 28 but are zero padded in our experiment to size 32 x 32. We set our batch size to 128 and the random noise vector, $z$, for the generator has size 128.

**Architecture**

| Layer type       | Input           | Output          |
|------------------|-----------------|-----------------|
| Dense layer 1    | 128, 32, 32, 1  | 128, 512        |
| Dense layer 2    | 128, 512        | 128, 512        |
| Dense layer output | 128, 512    | 128, 10         |

Table 1: Discriminator architecture

| Layer type       | Input           | Output          |
|------------------|-----------------|-----------------|
| Dense layer 1    | 128, 128        | 128, 512        |
| Dense layer 2    | 128, 512        | 128, 512        |
| Dense layer 3    | 128, 512        | 128, 1024       |
| Reshape output   | 128, 1024       | 128, 32, 32, 1  |

Table 2: Generator Architecture

**Learning rate**
The learning rate is set to 0.0005 and the discriminator’s loss is minimized 5 times per minimization of the generator’s loss similar to the original WGAN-GP paper.

**Training set**
The training set consists of 200 labelled training samples per class and 5000 unlabelled training samples per class.

**Test set accuracy scores**
A confusion matrix example for a single experiment of the testing samples can be seen below in Fig. 6

![Confusion Matrix](https://via.placeholder.com/150)

Figure 6: Confusion matrix of testing samples for semi-supervised MNIST experiment using WGANs-GP.

Test accuracy averaged over 10 runs $= 96.11\%$. 
Figure 7: TensorFlow code snippet of total loss given by eq. 4 within a WGAN class.
C Experimental setup for MNIST combined with Fashion-MNIST test

Architecture

| Layer type         | Input       | Output  |
|--------------------|-------------|---------|
| Dense layer 1      | 128, 32, 32, 1 | 128, 512 |
| Dense layer 2      | 128, 512    | 128, 512 |
| Dense layer 3      | 128, 512    | 128, 512 |
| Dense layer output | 128, 512    | 128, 10  |

Table 3: Discriminator architecture

| Layer type         | Input       | Output       |
|--------------------|-------------|--------------|
| Dense layer 1      | 128, 128    | 128, 512     |
| Dense layer 2      | 128, 512    | 128, 512     |
| Dense layer 3      | 128, 512    | 128, 512     |
| Dense layer 4      | 128, 512    | 128, 1024    |
| Reshape output     | 128, 1024   | 128, 32, 32, 1 |

Table 4: Generator Architecture

Learning rate
The learning rate is set to 0.0005.