RABLE: Rebalancing Data with Generative Method for Imbalanced Partial Label Learning

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Chapter 1

Introduction

Machine learning has achieved success in a wide range of applications, especially when models are trained with datasets containing accurate labels. These datasets, often referred to as "fully labeled" datasets, have been instrumental in training models for tasks such as classification and regression. However, the process of obtaining accurate labels can be a challenging and expensive endeavor. Labeling data requires human effort and resources, and in some cases, acquiring completely precise labels is simply unattainable, particularly in scenarios involving massive datasets or specialized domains. This necessity for precision in labeling is what has led to the emergence of the concept of weak supervision.

Weak supervision acknowledges that in many machine learning tasks, it is not always possible to possess labels that are entirely accurate or complete. Instead, it relies on partial, uncertain, or ambiguous labels. Machine learning models are expected to cope with this inherent uncertainty. Among the various methods within the domain of weak supervision, one that stands out is Partial Label Learning (PLL), where we have access only to candidate label sets for each example.

Partial Label Learning is a crucial subfield within the realm of weak supervision. It emphasizes the idea that we can only access candidate label sets for each example, introducing ambiguity and uncertainty as central features of the learning process. For instance, consider the need for precise labeling of an image, distinguishing between a Siberian tiger and a Bengal tiger. When annotators cannot accurately determine the image category, they may provide multiple candidate categories. The primary objective of PLL is to train a classifier capable of accurately predicting the correct labels for new, unlabeled data. As Figure 1.1 shown, "Siberian tiger" is more likely to be predicted as the category of the given input instance based on probabilities calculated by Partial Label Learning, compared with other candidate labels. Simultaneously, it addresses the challenges posed by ambiguous labels during the training process, with the aim of enhancing prediction accuracy.

PLL methods often incorporate advanced learning strategies to effectively handle situations where only partial labels are available. These strategies may include self-paced learning, self-training, and metric learning. However, it's important to note that traditional PLL methods typically treat label ambiguity as noise to be eliminated, and they strive to achieve

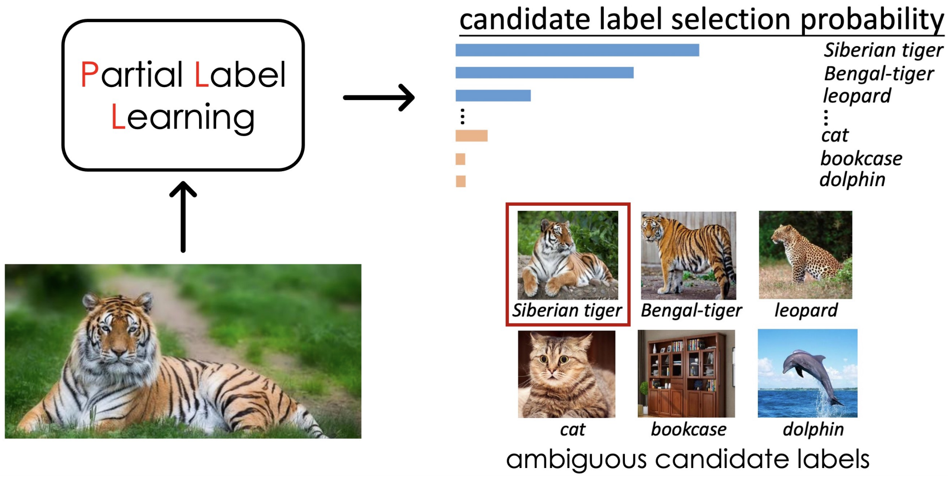

Figure 1.1: An example of a process based on Partial Label Learning. Given an input image, a list of candidate label selection probability would be generated through a trained classifier, showing the confidence of each category.

clarity in labeling. In contrast to traditional PLL methods, our project, called "RABLE: rebalancing data with generative method for imbalanced partial label learning," introduces a novel approach that embraces the uncertainty inherent in labels to enhance the performance of partial label learning. The core innovation of the RABLE method is based on contrastive learning, a technique that leverages label ambiguity to improve classification accuracy, particularly in cases where data distribution is imbalanced or skewed.

In the field of partial label learning, datasets that reflect real-world scenarios are often underutilized. This underutilization can be attributed to the complexity of these datasets, where labels are incomplete, introducing a layer of uncertainty and ambiguity that models must contend with. Additionally, obtaining high-quality partial label data can be a challenging task, often demanding significant time and resources. This is especially true in scenarios where data is scarce, such as in few-shot learning or when dealing with imbalanced data distributions. Furthermore, performance in partial label learning doesn't always align with that of standard supervised learning. This discrepancy often makes traditional fully labeled datasets more attractive to machine learning practitioners.

Our project sets out to address the challenges posed by data-hungry scenarios, with a particular emphasis on alleviating the imbalance inherent in partial labeling datasets. To achieve this, we propose a novel neural network model named RABLE. This model aims to enhance the performance of partial label learning by utilizing the contrastive learning architecture based on ABLE.

The ABLE baseline is a fundamental component of our approach. It leverages the principles of contrastive learning and partial-label learning to tackle the challenges of partial-label learning. Initial experimental results have demonstrated that the ABLE baseline exhibits robustness to a certain degree of data imbalance and inadequacy. However, as the degree of imbalance increases and the data distribution becomes more extremely skewed, the model's performance begins to decline.

To overcome this challenge, we employ generative methods as a means to enhance the data and rebalance the data distribution. This process involves several steps. First, we utilize language models to generate captions or descriptions for the imbalanced images. By introducing textual descriptions, we bridge the gap between visual and textual data representations. Subsequently, we generate synthetic images to rebalance the data distribution based on these text captions using generative models such as "Stable Diffusion." Finally, we combine these synthetic images with the original imbalanced images to create a rebalanced dataset for training. This generative pipeline functions as an add-on module for RABLE, serving the purpose of rebalancing data distribution when dealing with data imbalance. Our project is supported by an overall project flow chart that illustrates the implementation of this pipeline.

Our preliminary results offer promising insights, demonstrating the feasibility of our approach within our intended setting and task. Notably, our method surpasses the performance of the original ABLE baseline by a substantial margin. These early results highlight the potential impact of our work, particularly in industries and enterprises reliant on computer vision models. We believe that our proposed pipeline holds great potential for companies and businesses utilizing computer vision models in their products and services. The pipeline has the theoretical capacity to enhance the robustness of their existing systems, such as surveillance systems. Considering the significant market share that companies in this domain hold, there is a strong possibility that our project can transition seamlessly from a research endeavor to a practical application.

The structure of this report is as follows: In Chapter 2, we delve into the high cost of acquiring precise datasets, using a real-world market example to emphasize the importance and challenges of PLL. Chapter 3 reviews related work, encompassing PLL methods, contrastive learning, and the complexities of dealing with imbalanced datasets, especially in long-tailed distributions. Chapter 4 details our project's methodology and design, highlighting the innovations and strategies it employs. In Chapter 5, we present our experimental design and visual results, providing insights into the effectiveness of our approach. Additionally, the report concludes with an explanation of an interactive website, offering further engagement and exploration opportunities for interested readers.

Chapter 2

The Costly Quest for Precision: A Market Example with Data Analysis

In the realm of machine learning, the pursuit of precision is often an unwavering goal. Precisely labeled data, as we have seen in the previous chapter, forms the bedrock upon which powerful machine learning models are constructed. However, this quest for absolute precision is not without its challenges, particularly when considering the substantial costs involved. In this chapter, we delve into a real-world market example, supported by data analysis, to shed light on the formidable costs of obtaining fully labeled datasets. This analysis will serve to underscore the critical role of Partial Label Learning (PLL) as a pragmatic and cost-effective solution, providing a bridge between precision and practicality.

Imagine a prominent online marketplace, recognized for its vast and diverse product catalog, spanning categories from electronics and fashion to home and kitchen appliances. The organization is determined to enhance its product recommendation system to offer users an unrivaled shopping experience. Their goal is not just to categorize products but to delve into intricate details like brand, model, and subcategories within product types. The intention is clear: precise labeling for precise recommendations.

The data science team at this marketplace undertakes a comprehensive cost-benefit analysis to understand the implications of attaining such a level of precision. The aim is to balance the financial investment required against the anticipated gains in user engagement, satisfaction, and, ultimately, revenue.

- Data Labeling Costs:

  One of the primary cost components is the expenses associated with labeling data. The marketplace's data science team estimates that, on average, labeling a single product could range from $5 to $20, depending on the complexity of the product categories.

- Dataset Size:

  The marketplace boasts millions of products, each requiring meticulous labeling. To achieve the desired level of precision, the team estimates that labels for at least 100,000 products, covering a wide range of offerings, are essential.

- Time Frame:

  The process of labeling a substantial dataset of this magnitude is time-consuming. It could take several months, if not more, to complete the process. Time equates to money, and this extended timeline has its cost implications.

- Quality Control:

  Ensuring the accuracy and consistency of labels necessitates additional quality control processes. This includes reviewing, correcting, and validating labels. These quality control measures add to the overall cost.

- Maintenance Costs:

  The marketplace continually introduces new products. This demands ongoing labeling efforts to maintain precision. The data science team projects substantial annual labeling expenses, ranging from hundreds of thousands to millions of dollars.

To provide a tangible perspective, let's introduce some hypothetical figures:

Data Labeling Cost per Product:	$\$10$
Number of Products Requiring Labels:	$100,000$
Time Frame for Labeling:	6 months
Estimated Quality Control Cost:	$\$50,000$
Annual Maintenance Cost:	$\$500,000$

Using these figures, the cost of obtaining fully labeled data would be substantial:

Initial Labeling Cost:	$\$10 \times 100,000 = \$1,000,000$
Quality Control Cost:	$\$50,000$
Annual Maintenance Cost:	$\$500,000$

Over a three-year period, the cost of maintaining fully labeled data with ongoing labeling for new products would be:

$$
\begin{aligned}
&\text{Initial Labeling Cost:} && \$1,000,000 \\
&\text{Quality Control Cost:} && \$50,000 \times 3 = \$150,000 \\
&\text{Three Years of Maintenance:} && \$500,000 \times 3 = \$1,500,000
\end{aligned}
$$

This comprehensive cost analysis highlights the high expenses associated with obtaining fully labeled datasets. The initial investment exceeds one million dollars, and the annual costs can go beyond a million dollars. For many organizations, especially those in highly competitive markets, this could pose a significant financial burden.

As a result of these cost considerations, the data science team at the marketplace began exploring alternative strategies to enhance their recommendation system without overburdening the budget.

This is where Partial Label Learning (PLL) comes into play. It provides a practical solution that recognizes the impracticality of achieving absolute precision within budget constraints. By using partial, uncertain, or ambiguous labels, PLL offers a cost-effective way for machine learning models to leverage available data, significantly reducing costs. It strikes a balance between the pursuit of precision and the reality of limited resources.

The cost analysis clearly demonstrates that PLL is not merely a theoretical concept; it is a practical necessity. It enables organizations to harness the power of machine learning while being mindful of resource limitations and the exorbitant costs associated with obtaining fully labeled data. By embracing PLL, organizations can make cost-effective progress in enhancing their machine learning applications and achieving tangible results without excessive financial burdens.

Chapter 3

Related Work

3.1 Partial Label Learning

Recent PLL (Partially Labeled Learning) methods have primarily focused on label disambiguation, which involves identifying the true label from a candidate label set(Lv et al., 2020;[LXF+20] Feng et al., 2020;[FLH+20] Xu et al., 2021b [XQGZ21]).

Averaging-based disambiguation methods, such as those proposed by Cour et al., 2011[CST11] and Zhang and Yu, 2015[ZY15], treat all CLs of each instance equally and make predictions by averaging their model outputs. On the other hand, identification-based disambiguation methods, like the one introduced by Yu and Zhang[YZ16], treat the ground-truth label as a latent variable and aim to identify it.

In the context of deep learning, Lv et al.[LXF+20] proposed a classifier-consistent risk estimator and a progressive identification algorithm, while Feng et al.[FLH+20] derived risk-consistent and classifier-consistent methods through a statistical model. However, these methods often corrupt data without considering that CLs can be instance-dependent in practice.In a groundbreaking contribution, Xu et al.[XQGZ21] were the first to consider instance-dependent PLL and introduced VALEN, a method that recovers the latent label distribution by inferring the true posterior density using a Dirichlet density parameterized with an inference model. They also deduced the evidence lower bound for optimization. Nevertheless, it's worth noting that very few of these approaches have explored the concept of label ambiguity.

In this paper, our objective is to harness the potentially valuable information stemming from label ambiguity to enhance learning from partially labeled data.

3.2 Contrastive Learning

Contrastive learning is an approach dedicated to constructing a representation space where representations originating from the same instance are drawn closer together, while those from different instances are pushed further apart, as outlined by Khosla et al.[KTW+20]in 2020. This method involves generating positive and negative pairs for each instance to

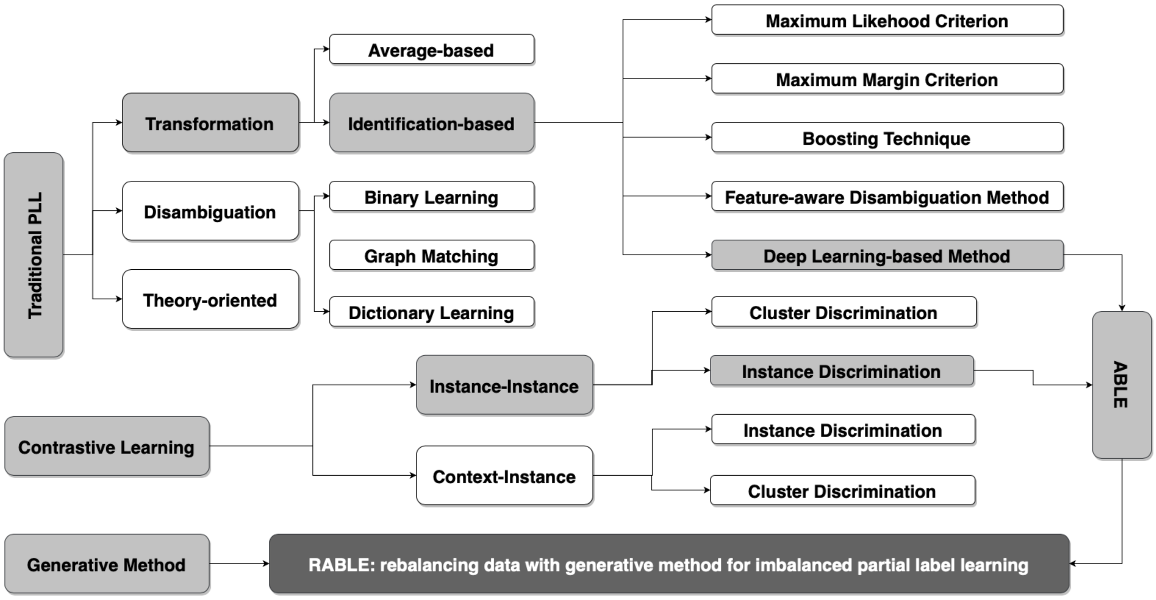

Figure 3.1: Overview of related work of RABLE.

construct the loss function.

Numerous studies have delved into its effectiveness in unsupervised representation learning, as evidenced by works by Chen et al.[CKNH20] in 2020 and He et al.[HFW+20] in 2020. More recently, Khosla et al.[KTW+20] in 2020 introduced Supervised Contrastive Learning, which incorporates explicit supervision by assembling data from the same class as the positive set. This success has spurred a wave of research endeavors that aim to apply contrastive learning to weakly supervised learning problems, as demonstrated in works such as that of Li et al.[LXH20] in 2021, among others.

3.3 Long-Tailed Learning and data augmentation

In real-world applications, training samples often exhibit a long-tailed class distribution, where a small number of classes have a large number of samples, while other classes are associated with only a few samples[LXH20, KLX+20, MJR+20, LMZ+19]. However, this class imbalance in the number of training samples poses significant challenges in training recognition models based on deep neural networks. To address the class imbalance, data augmentation which aims to enhance the size and quality of datasets by applying pre-defined transformations to each data / feature for model training[PW17, SK19] is a good idea.

In long-tailed learning, there are two types of augmentation methods that have been explored, i.e., transfer-based augmentation and non-transfer augmentation.Head-to-tail transfer augmentation seeks to transfer the knowledge from head classes to augment tail-class samples. For example, Major-to-Minor translation (M2m)[KJS20]proposed to augment tail classes by translating head-class samples to tail-class ones via perturbation-based optimization, which is essentially similar to adversarial attack.

The translated tail-class samples are used to construct a more balanced training set for model training. Besides the data-level transfer in M2m, most studies explore feature-level transfer. For instance, Feature Transfer Learning (FTL)[YYS+19] found that tail-class samples have much smaller intra-class variance than head-class samples, leading to biased feature spaces and decision boundaries.

To address this, FTL exploits the knowledge of intra-class variance from head classes to guide feature augmentation for tail-class samples, so that the tail-class features have higher intra-class variance. Similarly, LEAP[LSH+20] constructs "feature cloud" for each class, and transfers the distribution knowledge of head-class feature clouds to enhance the intra-class variation of tail-class feature clouds. As a result, the distortion of the intra-class feature variance among classes is alleviated, leading to better tail-class performance.

Non-transfer augmentation seeks to improve or design conventional data augmentation methods to address long-tailed problems. SMOTE [HWM05], a classic over-sampling method for non-deep class imbalance, can be applied to deep long-tailed problems to generate tail-class samples by mixing several intraclass neighbouring samples. Recently, MiSLAS [ZCLJ21] further investigated data mixup in deep long-tailed learning, and found that (1) data mixup helps to remedy model over-confidence; (2) mixup has a positive effect on representation learning but a negative or negligible effect on classifier learning in the decoupled training scheme[KXR+19]. Following these observations, MiSLAS proposed to use data mixup to enhance representation learning in the decoupled scheme.

Additionally, Remix [CCP+20] also employed data mixup for long-tailed learning and introduced a re-balanced mixup method tailored to improving the representation of tail classes.

3.4 Generative Method

Generative Models for Image Synthesis The high dimensional nature of images presents distinct challenges to generative modeling. Generative Adversarial Networks (GAN)[CWD+18] allow for efficient sampling of high resolution images with good perceptual quality[BDS18, KLA+20], but are difficult to optimize[GAA+17, MGN18] and struggle to capture the full data distribution[MPPSD16].

In contrast, likelihood-based methods emphasize good density estimation which renders optimization more well-behaved. Variational autoencoders (VAE)[KW13] and flow-based models[DKB14, DSDB16] enable efficient synthesis of high resolution images[Chi20, KD18, VK20], but sample quality is not on par with GANs.

Recently, Diffusion Probabilistic Models (DM)[SDWMG15], have achieved state-of-the-art results in density estimation[KSPH21] as well as in sample quality [DN21]. The generative power of these models stems from a natural fit to the inductive biases of image-like data when their underlying neural backbone is implemented as a UNet[DN21, HJA20, RFB15, SSDK+20]. The best synthesis quality is usually achieved when a reweighted objective[HJA20] is used for training. In this case, the DM corresponds to a lossy compressor and allow to trade image quality for compression capabilities.

Evaluating and optimizing these models in pixel space, however, has the downside of low inference speed and very high training costs. While the former can be partially adressed by advanced sampling strategies[KP21, SRNW21, SME20] and hierarchical approaches [HSC+22, VKK21], training on high-resolution image data always requires to calculate expensive gradients. Stable Diffusion[RBL+22] works on a compressed latent space of lower dimensionality. This renders training computationally cheaper and speeds up inference with almost no reduction in synthesis quality.

Chapter 4

Methodology

4.1 Overview of ABLE

ABLE is a novel approach to instance-dependent partial label learning that leverages label ambiguity to improve performance. The model consists of two key components: an ambiguity-induced positives selection mechanism and an ambiguity-induced contrastive learning method. The former selects instances that are predicted to belong to the same class as the anchor but have different candidate labels, which are called ambiguity-induced positives. The latter uses these positives to learn a representation pool (RP) and a projection function (g) that minimize a weighted ambiguity-induced loss. The weights are obtained by training a classifier (h) that minimizes a classification loss. The RP and CS are updated synchronously to break a circular dependency. The goal is to learn a classifier that can make correct predictions on unseen inputs, given a partially labeled training set. The input space is denoted as X, and the label space is denoted as Y = 1, 2, ..., c. The training set is denoted as $D = (x_k, S_k)|1 \leq k \leq M$, where x_k denotes the training instance and $S_k \subseteq Y$ denotes the candidate label set. The key definition of partial label learning is that the latent ground-truth label $y_k \in Y$ of an instance x_k is always included in its candidate label set.

4.2 Ambituity Induced Postives Selection

Ambiguity-induced positives selection is a mechanism used in ABLE to select instances that are predicted to belong to the same class as the anchor but have different candidate labels. This mechanism is designed to exploit the potentially useful information from label ambiguity in instance-dependent partially labeled learning. For each training instance (x_i, S_i) in the augmented batch, ABLE constructs various positives by considering each candidate label in S_i and selecting a group of samples currently predicted as that class as the ambiguity-induced positives. The class prediction is limited to be in the candidate label set S_i. This selection mechanism allows ABLE to leverage the noisy but valid information provided by candidate labels to improve performance. The ambiguity-induced positives are used in the subsequent ambiguity-induced contrastive learning method to learn a representation pool and a projection function that minimize a weighted ambiguity-induced loss. The weights

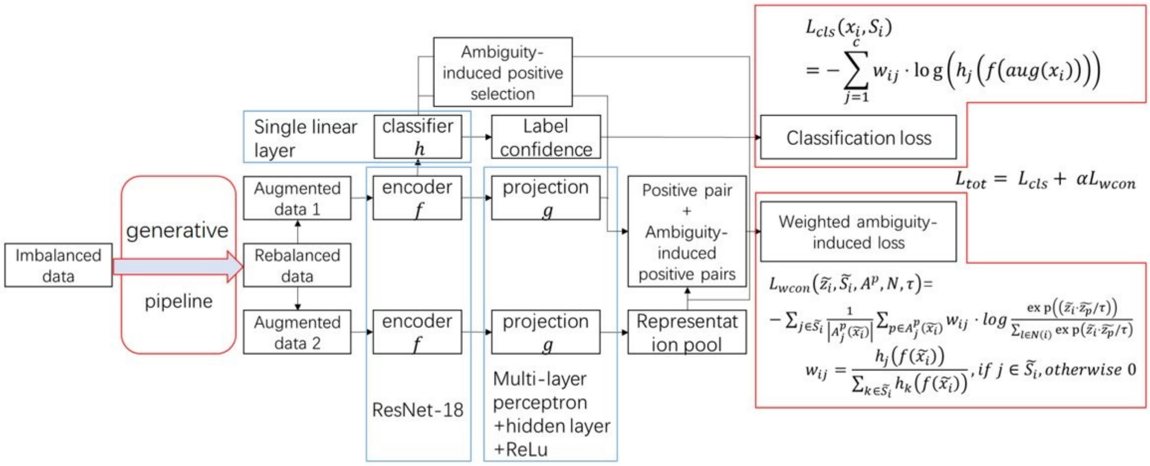

Figure 4.1: pipeline of RABLE

are obtained by training a classifier that minimizes a classification loss. The goal is to learn a classifier that can make correct predictions on unseen inputs, given a partially labeled training set.

4.3 Amiguity Induced Contrastive Learning

Ambiguity-induced contrastive learning is a key component of ABLE that is used to learn a representation pool and a projection function that minimize a weighted ambiguity-induced loss. This method is designed to exploit the noisy but valid information provided by candidate labels in instance-dependent partially labeled learning. After the ambiguity-induced positives selection, each training instance has multiple groups of ambiguity-induced positives. ABLE constructs ambiguity-induced pairs, which include the training instance and its corresponding ambiguity-induced positives, for the subsequent contrastive learning. The contrastive loss is used to pull the anchor and its ambiguity-induced positives closer in the representation space and push the remaining instances away.

The contrastive loss is defined as follows:

$$-log \frac{e^{(z_i \cdot z_p/\tau)}}{\sum_{P_l \in N(i)} e^{(z_i \cdot z_l/\tau)}}$$

where z_i and z_p are the representations of the anchor and its ambiguity-induced positive, respectively, τ is the temperature parameter, and $\cdot$ denotes the dot product. $N(i) = I\{i\}$ is the index set of the other representations originating from the same augmented batch. The goal is to minimize the contrastive loss for each ambiguity-induced pair, which can be achieved by updating the representation pool and the projection function.

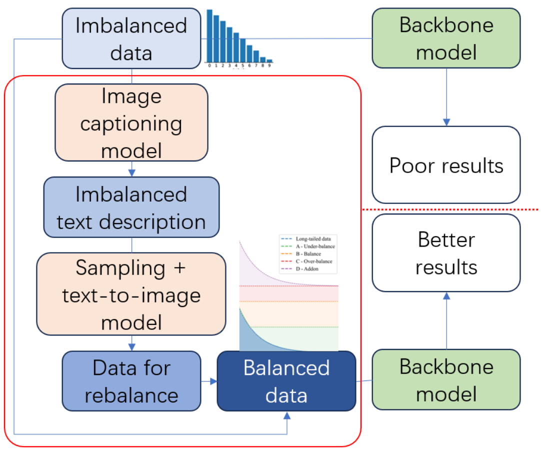

Figure 4.2: data rebalancing pipeline

The representation pool is learned by minimizing the following weighted ambiguity-induced loss:

$$L_{rp} = \sum_i \sum_p w_{i,p} L_c(z_i, z_p)$$

where w_i, p is the weight of the contrastive loss between the anchor and its ambiguity-induced positive, and L_c is the contrastive loss defined above. The projection function is learned by minimizing the following classification loss:

$$L_{cs} = \sum_i L_y(h(g(z_i)), y_i)$$

where h is the classifier, g is the projection function, and L_y is the cross-entropy loss. The goal is to learn a representation pool and a projection function that can minimize the weighted ambiguity-induced loss and improve performance on unseen inputs, given a partially labeled training set.

4.4 Data Rebalancing

The data hungry scenario significantly decreases the performance of ABLE model, so intuitively the solution of data rebalancing would work to reduce the influence of data imbalance. By utilizing pretrained BLIP-2 and StableDiffusion model, we can generate synthetic images of each imbalance class, so hopefully they can be restored to the original distribution.After rebalancing the data distribution, the rebalanced RABLE pipeline is demonstrated as in Figure 4.1.

Chapter 5

Visualization

5.1 Experiment

The experiments are conducted on CIFAR-10 dataset with an exponential imbalance factor of 0.01. In the process of data rebalancing, the number of images in each imbalance class is restored to the original balanced number. The experiments are based on backbone ResNet18.

Our method achieves a better performance on the test data of CIFAR-10 images. Compared to the baseline accuracy of 54.16%, our method achieves an accuracy of 66.58% on CIFAR-10 with an imbalance factor of 0.01.

We perform visual comparative analysis on ABLE as well as on our RABLE model separately. Specifically, we train the same number of rounds on ABLE and the brand new RABLE with the same hardware, after which the two models obtained are visualized and tested separately for comparative presentation. The test method is to select 100 images from the test dataset of Cifar-10, input the two models to get the predicted labels respectively, and compare them with the real labeled labels, and give two large 10x10 images respectively. The small colored images in the two figures indicate the correctly predicted parts, while the small black and white images indicate the incorrectly predicted images.

We can see that Figure 5.2 represents the test visualization results for ABLE as well as RABLE respectively. We can visualize that out of these 100 test images, ABLE's model predicted 56 correctly and 44 wrongly, which is not a very good result. Our RABLE model predicts 74 images correctly and only 26 images incorrectly, which is much better than ABLE without changing the training dataset and only relying on data augmentation.ABLE has a hard time to distinguish the pictures of cars, while our new model does a much better job in distinguishing the pictures of cars. However, the model also mispredicts subjects that are obvious to the human eye, so there is still a lot of room for improvement.

5.2 Interactive Website

To facilitate a better understanding of our project for users, we have developed a website with interactive features and displays.

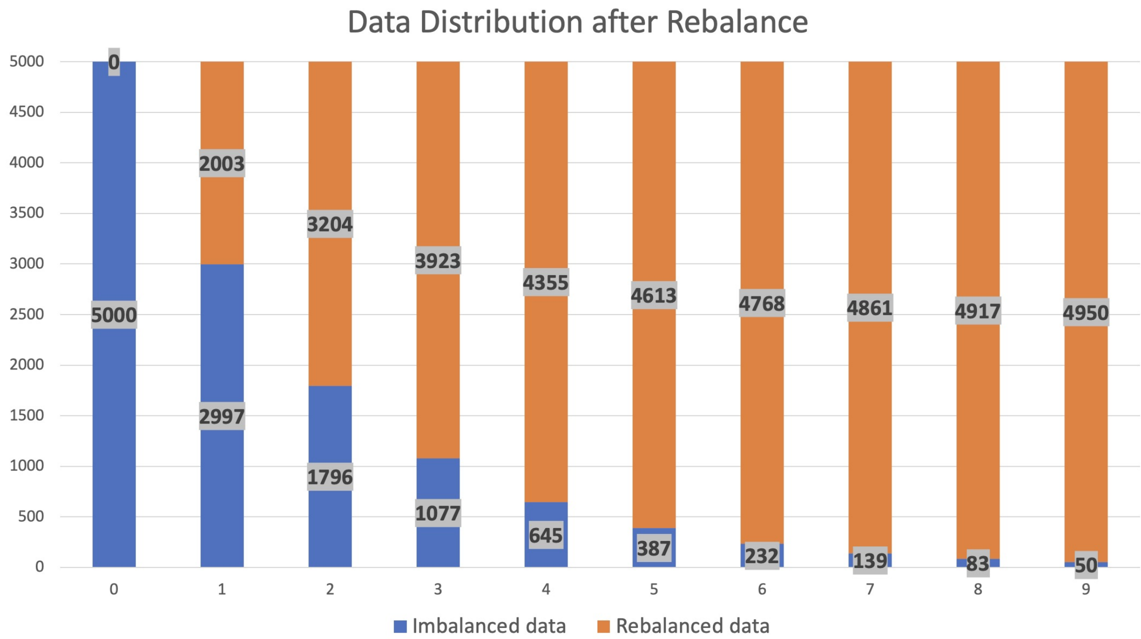

Figure 5.1: Rebalanced data distribution

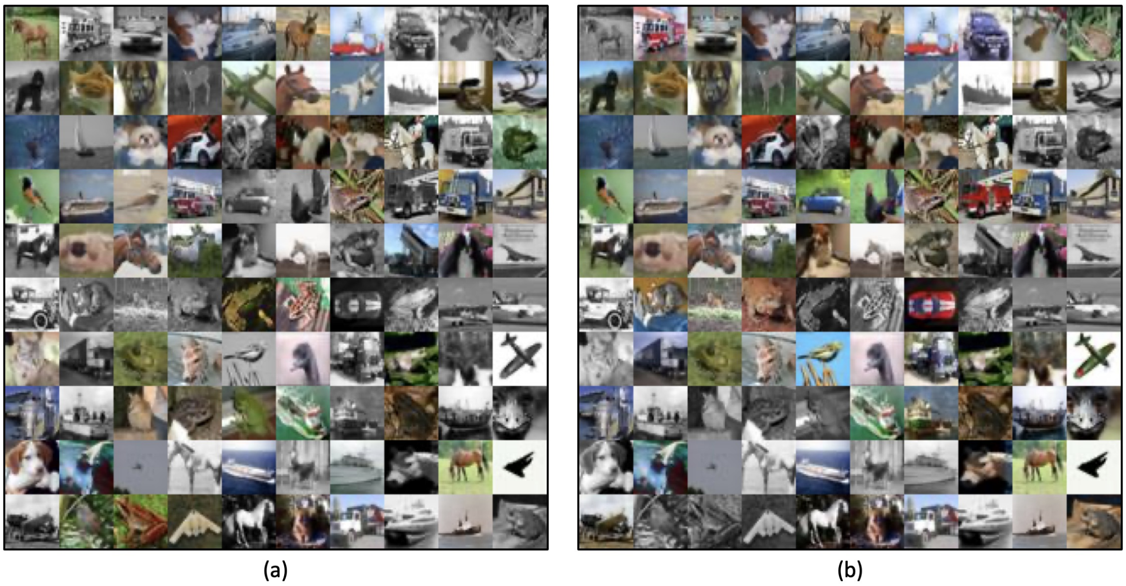

Figure 5.2: Visualization results. (a) shows the results for ABLE, while (b) shows the results for RABLE. For the figure of each model, the labels of the colored images are predicted accurately, while the labels of the black and white images are predicted incorrectly.

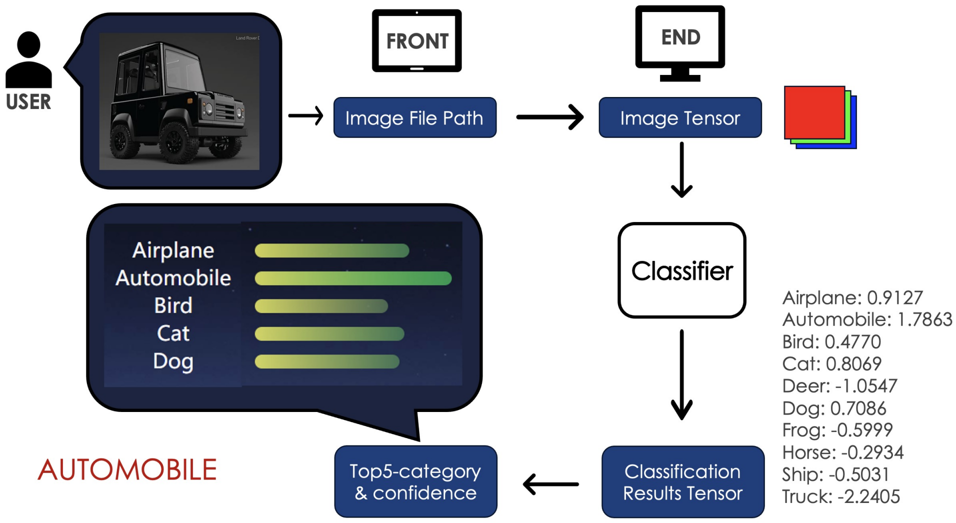

Figure 5.3: An example of using "Have a Try".

Users can navigate through the menu to access the homepage, report links, our GitHub page, and a demonstration video hosted on YouTube. We have provided concise videos and text materials to help users better understand RABLE.

We also have an interactive button called "Have a try!" that allows users to get hands-on experience with partial label image classification. After users upload an image and click the "Upload Image" button, the right side will display the top five most likely categories along with their confidence scores. Since our method is not entirely accurate, users can choose to provide feedback in the feedback box, and we would greatly appreciate it.

If a user uploads an image of a black car, as shown in Figure 5.3, and once the frontend receives the image, it passes the image's path to the backend. The backend then processes the image to create a feature vector, which is passed through a pre-trained classifier to obtain classification results, including confidence scores for each category. The backend then returns the top five categories and their confidence scores to the frontend. The frontend normalizes this information and displays it on the webpage. Consequently, the highest probability is associated with the "Automobile" category for this image. Specific installation and user guide are described in the appendix.

Chapter 6

Conclusion

In conclusion, "RABLE: Rebalancing Data with a Generative Method for Imbalanced Partial Label Learning" represents a significant breakthrough in the field of machine learning, particularly in addressing the challenges of Partial Label Learning within the context of imbalanced data distribution. Our approach, based on the innovative ABLE-IMB model, harnesses the power of generative methods and Contrastive Learning to enhance the resilience and performance of partial label learning.

Through this project, we have demonstrated the feasibility and effectiveness of our approach. Preliminary results have shown substantial improvements over the original ABLE baseline, especially in cases of data imbalance and skewed data distribution. This success opens up new possibilities for the practical application of our methodology in industries reliant on computer vision models, such as surveillance systems.

We believe that our work has the potential to bridge the gap between research and real-world implementation. The innovative use of generative methods to rebalance data and leverage label ambiguity provides a valuable solution for challenging scenarios in machine learning. Our project lays the groundwork for more accurate and robust predictions in situations where fully labeled data is scarce or unavailable.

As we move forward, our intention is to further refine and expand our approach. In the existing visual results, the small size of images has led to unsatisfying l classification outcomes. In the future, we will enrich the dataset, address the remaining challenges, and continue to validate its effectiveness. We anticipate that RABLE will continue to evolve and contribute to the advancement of machine learning techniques capable of handling weak supervision and imbalanced data with greater accuracy and reliability.

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GRADUATE CERTIFICATE: Intelligent Reasoning Systems (IRS)
PRACTICE MODULE: Project Proposal

Date of proposal:

2 Oct 2023

Project Title:

ISS Project – RABLE: rebalancing data with generative method for imbalanced partial label learning

Sponsor/Client: *(Name, Address, Telephone No. and Contact Name)*

Institute of Systems Science (ISS) at 25 Heng Mui Keng Terrace, Singapore
NATIONAL UNIVERSITY OF SINGAPORE (NUS)
Contact: Mr. GU ZHAN / Lecturer & Consultant
Telephone No.: 65-6516 8021
Email: zhan.gu@nus.edu.sg

Background/Aims/Objectives:

Machine learning has been successful in various tasks, like classification and regression, where models are trained with examples that have correct labels. However, getting accurate labeled data can be difficult and expensive. Hence, it is important for machine learning to work with less precise information, called weak supervision. There are different methods for weak supervision, and one of them is called Partial Label Learning (PLL), where we only have access to candidate label sets for each example.

PLL has found applications across diverse domains, including multimedia analysis, facial age estimation, web data mining, disease diagnosis, and more. PLL aims to learn a classifier that can predict the correct labels for new, unlabeled data accurately, clarifying ambiguous labels during training to make accurate predictions later. PLL methods often incorporate advanced learning strategies such as self-paced learning, self-training, and metric learning to effectively handle situations where only partial labels are available. Previous PLL methods see ambiguity as noise and try to eliminate it, while ABLE based on Contrastive Learning utilizes it although the classification would shift the classification towards the majority class under some certain conditions such as the long-tailed distribution.

Additionally, Partial Label Datasets are not widely adopted for several practical reasons, though they are closer to reality. Handling them is more complex than fully labeled datasets because the labels are incomplete, requiring models to deal with uncertainty and label ambiguity. Moreover, obtaining high-quality partial label data can be challenging, as it often demands considerable time and resources, and needs to consider the data hungry like few-shot or imbalanced data distribution. Performance in partial label learning may not always match that of standard supervised learning, making traditional labeled data more attractive.

Our project aims to rebalance data-hungry scenario, especially alleviating the imbalance of the partial labeling dataset through data augmentation, and to propose a new network model called ABLE-IMB to improve the performance of the partial labeling task by using the contrastive learning architecture based on ABLE.

Requirements Overview:

- Research ability
- Programming ability
- System integration ability

Resource Requirements (please list Hardware, Software and any other resources)

Hardware proposed for consideration:

- GPU, RaspberryPi, AlphaBot, NVidia Jetson Box, etc.

Software proposed for consideration:

- Reasoning systems, e.g. KIE jBPM, Drools, AppFormer, OptaPlanner, Fuzzy logic, Optimization, etc
- Pertained machine learning models, e.g. Vision, Speech, NLP
- Machine learning use cases, e.g. Orange3, R
- Deep learning tools, e.g. Neural Network Console Sony, Python Keras
- Chat-bots, e.g. ChatterBot, DBpedia Chat-bot
- Cognitive systems, e.g. MyCroft
- Robotic Process Automation, .e.g TagUI
- Cloud computing/server, e.g. Amazon, Google, IBM, Azure, etc.
- Application container, e.g. Docker

Number of Learner Interns required: (Please specify their tasks if possible)

a team of four project members

Methods and Standards:

Procedures	**Objective**	**Key Activities**
Requirement Gathering and Analysis	The team should meet with ISS to scope the details of project and ensure the achievement of business objectives.	1. Gather & Analyze Requirements 2. Define internal and External Design 3. Prioritize & Consolidate Requirements 4. Establish Functional Baseline
Technical Construction	· To develop the source code in accordance to the design. · To perform unit testing to ensure the quality before the components are integrated as a whole project	1. Setup Development Environment 2. Understand the System Context, Design 3. Perform Coding 4. Conduct Unit Testing

Integration Testing and acceptance testing	To ensure interface compatibility and confirm that the integrated system hardware and system software meets requirements and is ready for acceptance testing.	1. Prepare System Test Specifications 2. Prepare for Test Execution 3. Conduct System Integration Testing 4. Evaluate Testing 5. Establish Product Baseline
Acceptance Testing	To obtain ISS user acceptance that the system meets the requirements.	1. Plan for Acceptance Testing 2. Conduct Training for Acceptance Testing 3. Prepare for Acceptance Test Execution 4. ISS Evaluate Testing 5. Obtain Customer Acceptance Sign-off
Delivery	To deploy the system into production (ISS standalone server) environment.	1. Software must be packed by following ISS's standard 2. Deployment guideline must be provided in ISS production (ISS standalone server) format 3. Production (ISS standalone server) support and troubleshooting process must be defined.

Team Formation & Registration

Team Name: Group 19
Project Title (repeated): RABLE: rebalancing data with generative method for imbalanced partial label learning
System Name (if decided): RABLE: rebalancing data with generative method for imbalanced partial label learning
Team Member 1 Name: HE YUANYANG
Team Member 1 Matriculation Number: A0285691N
Team Member 1 Contact (Mobile/Email): 89423217/E1221503@u.nus.edu
Team Member 2 Name: Zhang Yixiao
Team Member 2 Matriculation Number: A0285937J
Team Member 2 Contact (Mobile/Email): zhangyixiao@u.nus.edu
Team Member 3 Name: Liu Zhiqian
Team Member 3 Matriculation Number: A0285884H
Team Member 3 Contact (Mobile/Email): 96145641/E1221696@u.nus.edu

Team Member 4 Name: Fan Hanwei
Team Member 4 Matriculation Number: A0286013L
Team Member 4 Contact (Mobile/Email): 89429311/E1221825@u.nus.edu

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Programme Name:	**Project No:**	**Learner Batch:**
Accepted/Rejected/KIV:		
Learners Assigned:		
Advisor Assigned: Contact: Mr. GU ZHAN / Lecturer & Consultant Telephone No.: 65-6516 8021 Email: zhan.gu@nus.edu.sg		

.1 Mapped System Functionalities against modular courses

In this secion, we aim to establish the connection between the functionalities of our project, RABLE, and the knowledge, techniques, and skills taught in the three fundamental modular courses of the IRS program: Machine Reasoning (MR), Reasoning Systems (RS), and Cognitive Systems (CGS). By examining our project's components in the context of the IRS curriculum, we can better understand how the project aligns with the key principles and methodologies introduced in these courses.

.1.1 Mapping to Machine Reasoning (MR)

Machine Reasoning provides a foundation in artificial intelligence fundamentals, knowledge representation, and automated reasoning. Our project leverages this knowledge to design a user-friendly web interface that embodies partial label learning. Users can upload images and receive classification results, exemplifying machine reasoning in practical use. Furthermore, our experiments reflect the principles of MR by assessing the effectiveness of our approach, demonstrating the translation of theoretical knowledge into real-world applications.

.1.2 Mapping to Reasoning Systems (RS)

Reasoning Systems delves into advanced reasoning techniques, including optimization, scheduling, and constraint satisfaction. Our project complements RS by applying optimization methods to rebalance data distributions in scenarios involving imbalanced datasets. We use generative models and data preprocessing techniques to enhance the performance of our partial label learning model, aligning with the concepts taught in RS. The practical implementation of these strategies is underscored by our experimental findings.

.1.3 Mapping to Cognitive Systems (CGS)

Cognitive Systems focuses on augmenting human capabilities through intelligent systems and human-computer interaction. Our project extends this idea by creating an interactive website that allows users to engage with the concept of partial label learning. Users can upload images, receive classification results, and provide feedback, facilitating their understanding of the technology. The integration of natural language processing and machine learning bridges the gap between visual and textual data, aligning with the principles taught in CGS. Additionally, our generative methods for rebalancing data distribution showcase how cognitive systems can enhance and optimize machine learning tasks.

In summary, our project links the theoretical knowledge gained in the IRS program to practical applications in the field of machine learning and reasoning. The detailed mappings provided in this chapter underscore how our work aligns with the knowledge domains introduced in the IRS curriculum.

.2 Installation and User Guide

.2.1 Installation using Conda

Using Anaconda, our project's environment configuration documentation can be rapidly imported into the conda environment.

```
conda env create -f environment.yml
```

.2.2 User Guide of Website

In the configured environment, open our project directory, and run the following command lines in the terminal.

```
python -m http.server
python app.py
```

Users must ensure that the port for running the backend file *app.py* matches the port for serving the frontend file *demo.html*.

Once everything is set up, you can access our website on localhost and start the "Have a try!" interactive experience. We've included some sample images in the project folder. For specific steps, you can refer to the example presented in Section 5.2 of the report under "Interactive Website." It's worth mentioning that a warning window will pop up when a user uploads an image with an incorrect format, which is designed to enhance the user experience in partial label learning for image classification tasks.

Master of Technology in Intelligent Systems

Individual Project Report

Your Name:	He Yuanyang
Certificate:	Graduate Certificate in Intelligent Reasoning Systems

1. Your personal contribution to the project.

Code implementation of RABLE model via Python and PyTorch;
Reproduction of ABLE model and results via Python and PyTorch;
Research into imbalance datasets;
Research into partial label learning and generative methods;
Making slides and presentation of the project;
Writing the methodology and experiment part of the project report

2. What you have learnt from the project.

I have learnt the use of python programming language and pytorch deep learning framework from this project in that I implemented the whole model pipeline from python and pytorch. Also, I have learnt about the academic research and academic writing techniques in the

3. How you can apply this in future work-related projects.

I can apply the project in future work-related projects in that I can use this generative pipeline for rebalancing imbalanced data distribution in future projects. Also, I can address the complicated situation in real-life low-quality datasets better according to my understanding of partial label learning and contrastive learning.
Apart from these, I can also apply what I learnt personally in future work-related projects. In this project, I learnt a lot about teamwork and communication, which I believe will be of great significance in future working situations.

Master of Technology in Intelligent Systems

Individual Project Report

Your Name:	ZHANG YIXIAO
Certificate:	Graduate Certificate in Intelligent Reasoning Systems

1. Your personal contribution to the project.

In our RABLE: Rebalancing Data with Generative Method for Imbalanced Partial Label Learning project, I have conducted preliminary research on our project, starting with an exploration of the academic landscape regarding the issue of label imbalance. Subsequently, I delved into an analysis of the current state of Contrastive Learning. In the following sections, I further investigated related work on long-tail distributions, data augmentation, and the development of generative models. This comprehensive review allowed us to assess the feasibility and necessity of our work.

Additionally, I have compiled and visually analyzed the comparative results between our model and the baseline. To do this, I extracted a subset of images from the CIFAR-10 dataset's test set and conducted comparative experiments. Images with correctly predicted labels were color-coded, while those with incorrect predictions were displayed in black and white. This visual representation significantly enhances the persuasiveness of our work.

Furthermore, I have integrated our trained model into a user-friendly interface, enabling users to input images and obtain predictions for different labels. By selecting the maximum prediction score, users can determine the model's predicted category, greatly improving the model's demonstrability.

2. What you have learnt from the project.

During the course of completing this project, I gained a profound understanding of many concepts that I had encountered in my academic coursework but hadn't fully comprehended. Firstly, through the process of research, I gained insight into the current state and potential applications of generative models in the academic world. I explored the various applications of cutting-edge models like Stable Diffusion, broadening my horizons regarding their usage.

Practical involvement in the project exposed me to the challenges arising from data imbalance and motivated me to learn diverse techniques to mitigate long-tail and data imbalance issues. For our project, we opted for using the Stable Diffusion model for data augmentation, ensuring our training data remained as balanced as possible, preventing issues like overfitting.

This research phase served as the initial and crucial step in commencing a scientific project. It laid a strong foundation for my future research work. Additionally, the process of training the model and debugging its functionality equipped me with hands-on experience in working with convolutional layers, pooling layers, various loss functions, and deep learning network architectures. I adeptly integrated these components within the PyTorch framework. Through this training process, I significantly improved my practical skills and my ability to employ deep learning for research exploration.

Working with images also enabled me to comprehend the impact of image channels and the influence of pixel data across different dimensions. Lastly, while composing the report, I honed my skills in adhering to the correct academic writing and citation conventions for scholarly papers.

3. How you can apply this in future work-related projects.

In my future endeavors and projects, I will begin by applying the valuable research experience I gained from this project. I will delve deeper into the current state of research within the academic community related to the tasks I intend to undertake. By accurately categorizing and consolidating the existing research findings, I will create comprehensive feasibility analysis reports. This approach will help me position my projects more effectively, enabling me to identify distinctive aspects that set my work apart from others. As a result, I aim to complete work that is not only independent but also highly innovative.

In the context of future deep learning projects, I will skillfully apply the experience I gained in utilizing the PyTorch framework and my expertise in image processing within the computer vision domain, which I acquired through this project. My documentation will become more lucid and code more structured and readable. Moreover, I am committed to enhancing the performance and quality of the models developed in future projects.

Lastly, I will maintain a rigorous and systematic approach to academic papers and reports, integrating the exacting standards instilled by my professors into my future work.

Master of Technology in Intelligent Systems

Individual Project Report

Your Name:	Liu Zhiqian
Certificate:	Graduate Certificate in Intelligent Reasoning Systems

1. Your personal contribution to the project.

Algorithm Design:
My involvement in algorithm design was instrumental in refining our project's image classification capabilities. This process demanded the thoughtful selection of machine learning algorithms and the creation of custom models for optimal classification accuracy. I worked closely with the team to implement and fine-tune these algorithms, ensuring our project's success.
Website Development:
Crafting an engaging and user-friendly website was a major responsibility. I took charge of designing, developing, and maintaining the project's front-end website, which served as the primary interface for uploading images and viewing classification results. This facet of my work ensured a seamless and visually appealing user experience. I was also involved in designing the "Have a Try" interactive feature for the RABLE system. This functionality allows users to upload images and receive real-time classification results. It's a valuable addition to the RABLE system, enhancing user engagement and making it more accessible to a wider audience.
Frontend-Backend Interface:
Establishing a robust interface between the frontend and backend systems was another key responsibility. I contributed by defining clear communication protocols, data transfer mechanisms, and data validation processes, ensuring smooth data flow throughout the system.
Market Research:
My active engagement in market research involved identifying potential use cases and target audiences for our project. Thorough market analysis gave our team a comprehensive understanding of market dynamics, ultimately shaping our project's strategy.
Case Study Selection:
I was responsible for curating and selecting case study images aligned with our project's objectives. This encompassed sourcing, organizing, and evaluating a diverse range of images, substantially enhancing our model's classification capabilities.
Promotion and Presentation Video:
Crafting the project's presentation video was an essential element of our promotional strategy. I was instrumental in scripting, recording, and editing the video to convey our project's vision and capabilities effectively.
Report Compilation:
I played a significant role in compiling the project report, which involved summarizing our project's goals, methods, and outcomes in a structured document.
Active Team Participation:
Throughout the project, I was actively involved in every team discussion and meeting. My participation included contributing ideas, providing constructive feedback, and collaborating effectively with team members to achieve project milestones.

2. What you have learnt from the project.

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Algorithm Design Insights: As a key player in algorithm design, I acquired a deep understanding of machine learning techniques. This experience was instrumental in selecting and fine-tuning algorithms, such as convolutional neural networks and deep learning models, to improve image classification accuracy. This knowledge has broadened my horizons in machine learning, paving the way for applying advanced algorithms to solve complex problems in the future.
Web Development Proficiency: My role in website development enabled me to master front-end technologies, including HTML, CSS, and JavaScript. I also became proficient in web design principles, user experience (UX) design, and responsive web development. These skills will be invaluable in future projects, especially when creating user-centric web interfaces or online platforms.
Frontend-Backend Integration: Establishing a robust frontend-backend interface was a technically demanding task. I gained expertise in API design and integration, data validation, and ensuring efficient data transfer. This technical insight into seamless system communication is a skill I will carry forward to ensure cohesive integrations in future projects.
Machine Learning Customization: The experience of customizing machine learning models has equipped me with the ability to tailor AI solutions to specific project requirements. This newfound skill will empower me to develop bespoke machine-learning solutions in future work contexts, ensuring that AI models align perfectly with project goals.
Promotional and Outreach Strategies: Engaging in promotional activities helped me understand the significance of effective marketing and outreach. I acquired skills in content creation, social media campaigns, and audience engagement. These skills will be invaluable when promoting future projects or products.
Effective Team Collaboration: My active involvement in team discussions and collaboration with diverse team members provided valuable insights into effective team dynamics and the importance of open communication, adaptability, and appreciation of varying perspectives.
Adaptability and Resilience: The project's dynamic nature necessitated adaptability and resilience in the face of evolving challenges. This experience enhanced my ability to remain flexible and composed in changing circumstances.

3. How you can apply this in future work-related projects.

Advanced Algorithm Implementation: I am now well-prepared to apply advanced machine learning and AI algorithms to solve complex real-world problems. Whether it's image recognition, natural language processing, or predictive modeling, I can harness the power of AI to drive project success.
User-Centric Design: The proficiency I gained in web development and frontend design will enable me to create user-friendly interfaces and applications that cater to the needs and preferences of end-users. I can ensure that the projects I undertake are not only technically robust but also visually appealing and easy to navigate.
Seamless Integrations: My experience in establishing frontend-backend interfaces has equipped me to facilitate smooth integrations between different components of a project. I will apply this skill to ensure that all systems work harmoniously, enhancing project efficiency.
Customized Machine Learning Solutions: I can now customize machine learning models to meet the specific requirements of a project. This will be particularly valuable in scenarios where off-the-shelf solutions do not fully align with project objectives.
Teamwork and Collaboration: Throughout this project, I have learned valuable lessons in teamwork and collaboration. I will carry forward this knowledge to foster effective teamwork in future projects.

Master of Technology in Intelligent Systems

Individual Project Report

Your Name:	Fan Hanwei
Certificate:	Graduate Certificate in Intelligent Reasoning Systems

1. Your personal contribution to the project.

In this project, my contributions were multi-faceted and played a crucial role in its overall success. My primary responsibilities included:

- Back-End Development:
  I took charge of developing the back-end code for our web system. This involved creating and structuring the server-side logic, ensuring seamless data flow between the front-end and back-end components, and defining the API specifications for communication.

- Front-End & Network Model Framework Collaboration:
  I actively participated in the design and implementation of the front-end of our web system. This included working closely with our front-end developer to ensure a cohesive and user-friendly interface. I also contributed to the framework design of our network model, which is central to our project. I provided valuable insights and suggestions, especially in the data acquisition phase, to enhance the overall model's effectiveness.

- Promotion Video and Report Editing:
  I played a role in the creation of our project's promotion video with Zhiqian, and I collaborated with my team members in the editing and refinement of the project report and related documentation.

- Test Case Selection and Case Study:
  I actively participated in the selection of test cases and the execution of case studies to evaluate the performance of our project.

2. What you have learnt from the project.

Intelligent Reasoning Systems provided a structured foundation, which I applied practically to tackle real-world problems using intelligent reasoning systems.

Master of Technology in Intelligent Systems

This project deepened my understanding of image classification, particularly in the context of partial label learning, shedding light on the challenges of dealing with uncertain and incomplete labels in real-world scenarios.

Participating in back-end development emphasized the importance of seamless front-end and back-end interactions in web systems. This experience broadened my skill set and highlighted the significance of interdisciplinary collaboration.

Assuming a leadership role within our group was a valuable personal growth experience. It honed my leadership, team coordination, and communication skills. I actively organized discussions, assigned tasks, and ensured regular progress updates.

This project's tight timeline improved my efficiency in planning and executing tasks. I learned to design and organize tasks effectively to maximize productivity within constrained timeframes.

3. How you can apply this in future work-related projects.

The knowledge and experiences gained from this project will be highly valuable in my future work-related projects.

I have developed a deeper understanding of image classification and partial label learning, which will boost my confidence and competence in machine learning projects. My structured knowledge of intelligent reasoning systems will serve as a foundation for applying AI and reasoning techniques systematically, enabling the design of intelligent systems for diverse applications. My hands-on experience in back-end development and collaboration with front-end developers has equipped me for full-stack development roles, ensuring smooth interactions between components. Furthermore, the leadership and team coordination skills I've honed will be crucial in managing teams in future projects, enhancing overall project efficiency. Efficient time management, another skill I've cultivated, will continue to be a cornerstone of my work, allowing me to meet deadlines while maintaining high-quality standards.

In sum, the skills and knowledge acquired in this project will significantly enhance my capabilities in the field of intelligent reasoning systems and in various other professional endeavors.