Knowledge Refinery: Learning from Decoupled Label

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\textbf{Abstract}

Recently, a variety of regularization techniques have been widely applied in deep neural networks, which mainly focus on the regularization of weight parameters to encourage generalization effectively. Label regularization techniques are also proposed with the motivation of softening the labels while neglecting the relation of classes. Among them, the technique of knowledge distillation proposes to distill the soft label, which contains the knowledge of class relations. However, this technique needs to pre-train an extra cumbersome teacher model. In this paper, we propose a method called Knowledge Refinery (KR), which enables the neural network to learn the relation of classes on-the-fly without the teacher-student training strategy. We define the decoupled labels, which consist of the original hard label and the residual label. To exhibit the generalization of KR, we evaluate our method in both fields of computer vision and natural language processing. Our empirical results show consistent performance gains under all experimental settings.

\textbf{Introduction}

Deep neural networks (DNNs) have recently been widely and successfully used in various tasks due to their powerful capabilities of extracting features. However, DNNs often contain millions of trainable parameters which easily cause the over-fitting problem. To solve this problem, many regularization methods including regularization on parameters (e.g., Dropout (Srivastava et al. 2014)), regularization on data (e.g., data augmentation), and regularization on labels (e.g., label smoothing(Srivastava, Greff, and Schmidhuber 2015)) have been developed to avoid over-fitting problems. Among them, parameter regularization methods need to modify and retrain DNN models, while data regularization methods require collecting a huge amount of training samples, both of which limit the practical value of DNNs in reality.

By contrast, label regularization methods (Szegedy et al. 2016; Pereyra et al. 2017; Bagherinezhad et al. 2018) are performed in a more friendly way and have recently received much attention, as they do not need to retrain/modify network structures. The general idea is that one-hot encoded labels are so hard which make DNN suffer from the over-fitting problem. In general, these methods can be further divided into two types of methods, label smoothing (Szegedy et al. 2016) and label softening based methods (Hinton, Vinyals, and Dean 2015). Label smoothing reduces the confidence score by uniformly redistributing 10\% of the weight from the ground-truth class to incorrect classes, while neglecting the knowledge of class-level relations (see Fig. 1(a)). For instance, an image of a “dog” that has similar visual appearance to a “cat” should have a higher label score than an image of a “plane” that has different visual appearance. To make labels more informative, label softening based methods attempt to extract the visual relations between classes to impose such knowledge into the training phase. Typical methods of this type are knowledge distillation methods (Hinton, Vinyals, and Dean 2015) that generate soft labels from a cumbersome teacher model to train a small student model (see Fig. 1(b)).

![Figure 1](image-url)
Although these existing label regularization methods relieve the over-confidence problem with soft labels, they may suffer from the under-confidence problem when the target label is over-smoothed. Therefore, they all have to adjust trade-off hyper-parameters to avoid over-/under-confidence problems. Overall, we can conclude that the “ideal” label regularization method should satisfy the following conditions: (i) Relation expression. The representation of labels consider the relation of classes. (ii) Online training. Learning the relation of classes on-the-fly without pre-training an extra teacher model. (iii) Flexibility. There is no need to adjust the softness of label representation.

To this end, we propose a novel label regularization method, called Knowledge Refinery (KR), by learning the knowledge of class-specific information and class-level relations dynamically. We decouple the “ideal” label into two components, the target label (i.e., the hard label or the smooth label) and the non-target label (i.e., the residual label), as is shown in Fig. 1(c). More specifically, instead of directly updating the target label, we update the residual label during training iteratively by the proposed knowledge refinery regularizer module. Compared with the technique of knowledge distillation (KD) which requires an extra teacher model, KR produces dynamical and informative labels on-the-fly. Overall, KR satisfies all the above conditions of the “ideal” label regularization method — Relation expression, Online training, and Flexibility. Furthermore, KR can serve as a universal regularizer and can be equipped into arbitrary vanilla deep neural networks.

The main contributions can be summarized as follows:

- We propose a new label regularization method, called knowledge refinery (KR), to enable networks to learn more informative knowledge from decoupled labels, which consists of hard label and residual label.
- We propose a mutual learning strategy to learn the relation of classes on-the-fly without teacher models. The extra memory and time consumption of our method are negligible in practice.
- The proposed KR regularizer serves as a plug-n-play module and can be equipped into an arbitrary vanilla DNN. The comprehensive experiments on different public benchmark datasets for image/text classification tasks verify the effectiveness of our method.

Related Works

Knowledge Distillation

Previous research on knowledge distillation (Hinton, Vinyals, and Dean 2015; Lopez-Paz et al. 2015; Zhu, Gong et al. 2018; Zhang et al. 2018; Wang, Liu, and Tao 2020) explored the transmission from deep and cumbersome teacher models to shallow and light student models. The rationale behind this technology is to ensemble the information distilled by one or more teacher models as extra supervision for the student model. Hinton et al. (2015) first applied soft labels produced by a teacher model to train a small student model. The soft label refined by the teacher model is defined as

\[ q_i^{\text{soft}} = \frac{\exp(z_i \beta)}{\sum_{j=1}^{K} \exp(z_j \beta)} \]

where \( K \) is the number of categories and \( T \) is a temperature that controls the smoothness of the soft label. With the technique of knowledge distillation, the student model can learn from the cumbersome teacher model and therefore improves the performance. In contrast, our method is more efficient without the teacher-student training strategy, and the hyper-parameter in our loss function is insensitive in practice.

Label Regularization

There exist different types of regularization methods to improve the generalization of neural networks, including (i) regularization on model parameters like Dropout (Srivastava et al. 2014; Zoph et al. 2018; Wan et al. 2013), (ii) regularization on model inputs like data augmentation, (iii) regularization on features like batch normalization and group normalization (Ioffe and Szegedy 2015), and (iv) regularization on labels like label regularization (Szegedy et al. 2016; Xie et al. 2016; Lee et al. 2018; Müller, Kornblith, and Hinton 2019; Xu et al. 2020; Chen et al. 2020). Among them, regularization methods on model parameters need to change the network structure and retrain the model, while they model inputs need to create a huge number of training samples. In contrast, regularization methods on labels are more efficient and train-friendly without the need of modifying network structures/inputs. In contrast to these methods, our method regularizes labels by learning the relations of labels using negligible extra computation consumption.

Preliminary

In this paper, we consider a \( K \)-class classifier \( h_\theta(x) : \mathcal{X} \to \mathcal{C} \), parameterized by \( \theta \), where \( \mathcal{X} \) is the input space and \( \mathcal{C} = \{1,...,K\} \) is the label space. Assuming the classifier \( h = g \circ f \) can be decomposed into two embedding functions, one is \( f_\theta : \mathcal{X} \to \mathcal{Z} \), which convert input features to logit vectors \( z = f_\theta(x) \), and the other one is the softmax layer \( g : \mathcal{Z} \to \mathcal{C} \), which converts logit vectors to the specific category. The cross-entropy loss (CE) function is

\[ L_{CE}(p, q) = -\sum_{i=1}^{K} p_i \log q_i, \]

where \( p = \text{softmax}(z) \), and \( q \) is the label vector like the one-hot encoded vector. Kullback-Leibler (KL) divergence is

\[ D_{KL}(p||q) = \sum_{i=1}^{K} p_i \log \left( \frac{p_i}{q_i} \right). \]

Jensen-Shannon (JS) divergence is

\[ D_{JS}(p||q) = \frac{1}{2} D_{KL}(p||\frac{p+q}{2}) + \frac{1}{2} D_{KL}(q||\frac{p+q}{2}). \]

Rethink Knowledge Distillation

In this section, we introduce some observations which motivate us to decouple the label. Let us review the loss function by knowledge distillation method (Hinton, Vinyals, and Dean 2015), which add a KL divergence loss term to the original cross-entropy loss function as follows:

\[ L_{KD} = (1 - \alpha) L_{\text{hard}} + \alpha T^2 L_{\text{soft}} \]

(1)

where \( L_{\text{hard}} = L_{CE}(p, q) \) and \( L_{\text{soft}} = D_{KL}(p||q^{(soft)}) \)

(2)

where \( \alpha \) is a trade-off parameter and \( T \) is the temperature factor. Let us rethink this loss function \( L_{KD} \). Given a model to recognize images belong to three classes “cat”, “dog”,
“plane”. Supposing the soft label $q$ of this “cat” image is $[0.6, 0.3, 0.1]$, which is learned by the teacher model. And suddenly the confidence probabilities $p$ predicted by the model for this image is $[0.7, 0.2, 0.1]$. As a result, we know that $L_{soft}$ would force the output $p$ close to the soft label $q$. That is, $L_{soft}$ attempt to decrease the confidence probability of “cat” from 0.7 to 0.6. By contrast, $L_{hard}$ (i.e. the cross-entropy loss based on the one-hot encoded label) would force the confidence probability of “cat” from 0.7 close to 1.0. We can naturally find that the optimization objective of $L_{soft}$ and $L_{hard}$ in the loss function $L_{KD}$ is contradictory in this case. In other words, the model trained with $L_{KD}$ may struggle with the balance of under- and over-confidence problem.

We also observed the learned soft labels and got some interesting findings. Take CIFAR-10 dataset for an example, we obtain the soft labels of all categories by the following steps: (i) We save the predicted probability $p_i = \text{softmax}(z)$ for each sample $i$. (ii) Calculate the soft label $\hat{q}_k$ of category $k$ by $\hat{q}_k = \frac{1}{|T_k|}\sum_{i \in T_k} p_i$, where $T_k$ denotes the set of samples of category $k$. Afterwards, we can obtain the soft labels of $K$ categories and each $\hat{q}_k$ is a vector of size $K$. That means we can use a matrix of size $K \times K$ to represent these soft labels.

In Fig. 2 (the first row), we give the visualization of the soft labels of categories learned after 1, 10, 200, and 300 epochs.

As we can see, the soft labels become harder with regard to the increasing epochs, and finally the probabilities of the ground-truth labels (diagonal) almost dominate the whole heatmap. To expose the probabilities of non-ground-truth labels (non-diagonal), we attempt to mask the ground-truth position $k$ in the calculation of softmax function as follows:

$$z^{(res)} = (z)_T,$$

$$p^{(res)} = \text{softmax}(z^{(res)}),$$

where $(z)_T$ means to mask the $k$-th position of $z$. The masked probability $p^{(res)}$ is called residual output in this paper. Afterwards, we use the same strategy to calculate the masked soft labels (i.e. residual label) of categories on $p^{(res)}$ as $\hat{q}_k^{(res)} = \frac{1}{|T_k|}\sum_{i \in T_k} p_i^{(res)}$, and the visualization can be seen in Fig. 2 (the second row). As a result, we can surprisingly find that (i) the heatmaps keep soft consistently from the beginning to end, (ii) the heatmaps have fairly well consistency, which means that the relation of labels can be learned fairly well even after only one epoch. Based on these findings, we think that the masked soft label is a better representation than the soft label.

Overall, the non-diagonal disappearance of the heatmaps in the first row and the softness consistency of the heatmaps in the second row motivated us to explore the masked soft label (i.e. residual label). To this end, we decouple the original label to two components — hard label and residual label. Here the hard label means the original one-hot encoded label which represents the specific-class information, and the residual label means the masked soft label which represents the class-level relations. The main advantages of decoupled labels include the following aspects: (i) there is no need to set hyper-parameter to trade-off the hard loss and the soft loss since the hard label and the residual label can complement each other well. (ii) the softness consistency allows us to design a regularization strategy for the residual label. We will introduce the details of our proposed regularizer in later sections.

**Knowledge Refinery**

Our **Knowledge Refinery** (KR) method aims to regularize the neural networks on-the-fly during the training phase. In
Figure 3: Pipeline of Knowledge Refinery with decoupled labels — the residual label $q^{(res)}$ and the hard label $q$.

In general, KR can be treated as a plug-n-play regularizer module, which can be unified into an arbitrary vanilla DNN, such as AlexNet (Krizhevsky, Sutskever, and Hinton 2012), VGG(Simonyan and Zisserman 2014), and ResNet (He et al. 2016a), as is shown in Fig. 3.

Workflow
The KR framework briefly consists of two modules — Original Neural Network and Knowledge Refinery Regularizer.

Original Neural Network The module of Original Neural Network is a vanilla neural network supervised by one-hot encoded labels (i.e. hard label). The loss of this module is the cross-entropy loss between the predicted probabilities $p$ and one-hot encoded labels $q$, which is typically as $L_{hard} = L_{CE}(p, q)$ (i.e. hard loss).

Knowledge Refinery Regularizer The module of Knowledge Refinery Regularizer works on the logits $z$ outputed by Original Neural Network. Firstly, recall the definition of residual label in previous section, we mask the $k$-th position of $z$, where $k$ represents the target class index. Next, as is shown in Eq. 3 and Eq. 4, we normalize the masked logits $z^{(res)}$ using the softmax function, and then we obtain the predicted residual probability $p^{(res)}$. On the other side, we adopt an embedding layer whose weight is a matrix $S \in \mathbb{R}^{K \times K}$, which represents Residual Correlation Matrix. Then we can directly obtain the residual label of category $k$ by adopting softmax normalization on the $k$-th row of $S$ as follows:

$$q^{(res)} = \text{softmax}(S_k).$$  \hspace{1cm} (5)

The loss of Knowledge Refinery Regularizer composes of residual loss and update loss. More specifically, the residual loss $L_{res}$ and the update loss $L_{upd}$ is a pair of mutual learning losses, the definition of which is as follows:

$$L_{res} = D_{KL}(p^{(res)}||q^{(res)}),$$  \hspace{1cm} (7)

$$L_{mut} = L_{upd} + L_{res}.$$  \hspace{1cm} (8)

Note that we initialize Residual Correlation Matrix to zero-filled matrix. That means the initial residual labels of categories are uniform distributions. The overall workflow can refer to Alg. 1. By this mutual learning strategy, we allow the backbone network and Residual Correlation Matrix learn from each other simultaneously. Moreover, recall the observed softness consistency of the residual label which is mentioned before, this mutual learning strategy also enable the model to avoid “consistency shift” by stabilizing the learned residual probabilities $p^{(res)}$.

Backward Propagation
In the mutual learning strategy, we aim to use $L_{upd}$ to update the residual labels derived from $S$ and use $L_{res}$ to regularize the backbone network $f_\theta$ via the learned residual probabilities $p^{(res)}$. Therefore, we block the useless gradients in $L_{upd}$ and $L_{res}$ in the backward-propagation phase, respectively. Specifically, we propagate the gradient of $L_{upd}$ only to the embedding layer $S$ by blocking the gradient of $p^{(res)}$ in Eq. 6. Same for the backward-propagation of $L_{res}$, we block the gradient of $q^{(res)}$ in Eq. 7 so that $L_{res}$ only affects the backbone network $f_\theta$. With this backward-propagation mechanism, $p^{(res)}$ and $q^{(res)}$ can be learned mutually. The overall loss is simply the linear summation of $L_{hard}$ and $L_{mut}$ as follows:

$$L_{tot} = L_{hard} + \alpha L_{mut}.$$  \hspace{1cm} (9)

Objective
In this section, we respectively analyze the objective of the backbone network $f_\theta$ and Residual Correlation Matrix $S$ based on the aforementioned backward-propagation mechanism. For the backbone network $f_\theta$, the objective can be
Algorithm 1 Workflow of Knowledge Refinery

1: $S \leftarrow 0$ ▷ Initialize the residual correlation matrix with zero matrix.
2: for epoch $= 1, 2, \ldots$ do
3: $z = f_{\theta}(x)$ ▷ Here we omit mini-batch for simplicity.
4: $\hat{p} = \text{softmax}(z)$
5: $L_{\text{hard}} = L_{CE}(p, q)$ ▷ Calculate the hard loss.
6: $z_{\text{(res)}} = (z)_{k}$ ▷ $k$ is the index of the ground-truth class,
7: $p_{\text{(res)}} = \text{softmax}(z_{\text{(res)}})$
8: $q_{\text{(res)}} = \text{softmax}(S_k)$
9: $L_{\text{upd}} = D_{KL}(q_{\text{(res)}} || p_{\text{(res)}})$ ▷ Calculate the update loss.
10: $L_{\text{res}} = D_{KL}(p_{\text{(res)}} || q_{\text{(res)}})$ ▷ Calculate the residual loss.
11: $\theta \leftarrow \theta - \beta \nabla L_{\text{hard}} + \alpha L_{\text{res}}$ ▷ Optimize the backbone network.
12: $S \leftarrow S - \beta \nabla \alpha L_{\text{upd}}$ ▷ Optimize the residual correlation matrix.
13: end for

formulated as follows:

$$\arg \min_{\theta}(L_{\text{hard}} + \alpha L_{\text{res}}).$$

On the other side, the objective of Residual Correlation Matrix $S$ can be formulated as follows:

$$\arg \min_{S}(\alpha L_{\text{upd}}),$$

where $\alpha$ is a hyper-parameter. In practice, we set the hyper-parameter $\alpha$ to an exponentially decreasing function $\alpha = \gamma^t$, where $t$ denotes the number of epochs and $\gamma$ is the decay factor which is set to 0.99 empirically. As is mentioned in previous section, the hard loss and the residual loss can be complement each other well, therefore there is no need to trade-off these two losses. Our experiments also show that the value of $\gamma$ is insensitive to the performance in the later section. For the theoretical analysis on the effectiveness of knowledge refinery, please refer to Appendix A.

Label Smoothing Enhanced KR

Label smoothing (Szegedy et al. 2016) proposed a mechanism for encouraging the model to be less confident about ground-truth to improve generalization. Typically, the smooth label $q_{\text{(smooth)}}$ gives 10% confidence of the ground-truth class to incorrect classes uniformly as

$$\begin{align*}
q_i^{(\text{smooth})} &= 0.9 \quad i = k, \\
q_i^{(\text{smooth})} &= 0.1 \quad i \neq k,
\end{align*}$$

In our method, we can easily apply the technique of label smoothing by replacing the hard label to the smooth label. After enhancing by label smoothing, the over loss Eq. 9 will be changed as

$$L_{\text{tot}} = L_{\text{smooth}} + \alpha L_{\text{mut}}.$$
mixed precision training (Micikevicius et al. 2017) in ImageNet experiments which offers significant computational speedup.

**Results on CIFAR.** The results on two CIFAR datasets are shown in Table 1. In each baseline, we trained the backbone network with only the one-hot encoded label. We compare our proposed knowledge Refinery (KR) and label smoothing enhanced knowledge refinery (KR-LS) with label smoothing (LS) and baselines, of which the best results are marked in bold. As we can see, LS, KR, and KR-LS all outperform baselines of different network structures. Moreover, KR achieves competitive gains over LS, and KR-LS obtains the best performance in all cases consistently, which shows the well complementarity between KR and LS. All these observations verify the effectiveness of KR and KR-LS. Specifically, KR-LS achieves 2.04% improvement over the baseline with ResNet-18 model on CIFAR-100 dataset. Note that our KR-based methods improve the performance with only adding negligible parameters to the original neural network. For a $K$-class task, the extra memory consumption of KR-based methods is $O(K^2)$. Compared with the huge number of parameters of the backbone network, this consumption is exactly negligible. In addition, the training curve is shown in Fig. 4 (Right). We also visualize $D_{JS}(p^{(res)} || q^{(res)})$ in Fig. 4 (Left) to show our KR regularizer make $p^{(res)}$ and $q^{(res)}$ closer during training, which is what we expect.

**Results on ImageNet.** For the huge ImageNet-12 dataset, the overall results are shown in Table 2, where the Top-N error rate is the fraction of test images for which the ground-truth label is not among the N labels considered most probable by the model. As we can see, compared with the baselines, KR and KR-LS can consistently improve the Top-1 and Top-5 error rate in all cases. Specifically, KR-LS method achieves the best performance which has 1.06% Top-1 and 0.82% Top-5 improvement over those of the baselines in all cases with ResNet-152 model.

**Text Classification**

**Datasets.** We use three benchmark datasets of text classification in our evaluations: (i) AGNews (Del Corso, Gulli, and Romani 2005): A topic classification dataset over 4 categories. (ii) Yahoo! Answers\(^1\): A topic classification dataset over 10 categories. (iii) Yelp Review Full\(^2\): A dataset of sentiment classification in which polarity star labels ranging from 1 to 5.

**Settings.** For all datasets, we evaluate knowledge refinery regularizer on four general models for text classification, including FastText (Joulin et al. 2017), TextRNN (Lai et al. 2015), CharCNN (Zhang, Zhao, and Lecun 2015), and Transformer (Vaswani et al. 2017). We compare the baseline and KR-LS in all experiments. The baseline of each model denotes the original network with only hard loss.

**Results.** The results are shown in Table 3. As we can see, KR-LS can improve the performance under all settings consistently. These experiments exhibit the generalization of our KR method no matter with which backbone network. Therefore, we believe that KR regularizer can be equipped to arbitrary hard label-based methods to improve the performance.

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\(^1\)https://webscope.sandbox.yahoo.com  
\(^2\)https://www.yelp.com/dataset
Therefore, the performance of KR-LS here is slightly lower than the results in Table 1.

We further compare KR-LS with two well-known settings with the least parameters. (ii) Although KD pre-trains an extra teacher model which provides extra knowledge to the student network, and DML trains two identical model simultaneously with double parameters, KR-LS achieves more performance gains over KD and DML.

Results. The results are shown in Table 4, from which we can observe: (i) KR-LS outperforms KD and DML under all settings with the least parameters. (ii) Although KD pre-trains an extra teacher model which provides extra knowledge to the student network, and DML trains two identical model simultaneously with double parameters, KR-LS achieves more performance gains over KD and DML.

Sensitivity Analysis
Settings. In this section, we aim to demonstrate the robustness of the only hyper-parameter in KR (i.e. \( \alpha \) in the loss function Eq. 9). Recall that we set \( \alpha \) to a exponentially decreasing function \( \alpha = \gamma^{t} \), where \( t \) denotes the number of epochs. To evaluate the robustness of \( \gamma \), we set \( \gamma \) to \([0, 0.9, 0.99, 0.995]\) and test the performance of each setting. Note that the setting of \( \gamma = 0 \) is equivalent to the baseline. In addition, we also set \( \gamma \) to a truncation function as follows:

\[
\gamma = \begin{cases} 
1 & \text{epochs} < 20, \\
0 & \text{epochs} \geq 20, 
\end{cases}
\]  

which we called \( 1^{*} \) for simplicity. All settings of \( \gamma \) are shown in Fig. 5 (Right). We conduct all experiments with ResNet-18 model on CIFAR-100 datasets.

Conclusion
In this paper, we propose Knowledge Refinery (KR), which regularizes DNNs with decoupled labels. The motivation of decoupling the label is the observed softness consistency of the residual label. Extensive experiments on different datasets and different backbone networks consistently show the performance gains over baselines with only negligible memory computation. In the future, we will further investigate the following aspects: (i) exploring how to apply decoupled labels to multi-label tasks, (ii) investigating the theoretical guarantee for KR and decoupled labels.

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