Moderately supervised learning: definition and framework

Yongquan Yang 1a, Zhongxi Zheng 2a, *

*Laboratory of Pathology, West China Hospital, Sichuan University, 37 Guo Xue Road, 610041 Chengdu, China

Abstract—Supervised learning (SL) has achieved remarkable success in numerous artificial intelligence applications. In the current literature, by referring to the properties of the ground-truth labels prepared for a training data set, SL is roughly categorized as fully supervised learning (FSL) and weakly supervised learning (WSL). FSL concerns the situation where the training data set is assigned ideal ground-truth labels, while WSL concerns the situation where the training data set is assigned nonideal ground-truth labels. However, solutions for various FSL tasks have shown that the given ground-truth labels are not always learnable, and the target transformation from the given ground-truth labels to learnable targets can significantly affect the performance of the final FSL solutions. Without considering the properties of the target transformation from the given ground-truth labels to learnable targets, the roughness of the FSL category conceals some details that can be critical to building the optimal solutions for some specific FSL tasks. Thus, it is desirable to reveal these details. This article attempts to achieve this goal by expanding the categorization of FSL and investigating the subtype that plays the central role in FSL. Taking into consideration the properties of the target transformation from the given ground-truth labels to learnable targets, we first categorize FSL into three narrower subtypes. Then, we focus on the subtype moderately supervised learning (MSL). MSL concerns the situation where the given ground-truth labels are ideal, but due to the simplicity in annotation of the given ground-truth labels, careful designs are required to transform the given ground-truth labels into learnable targets. From the perspectives of definition and framework, we comprehensively illustrate MSL to reveal what details are concealed by the roughness of the FSL category. Finally, discussions on the revealed details suggest that MSL should be given more attention.
1. Introduction

With the development of fundamental machine learning techniques, such as deep learning [1], supervised learning (SL) has achieved great success in various classification and regression tasks for artificial intelligence. Typically, a predictive machine learning model is learned from a training data set that contains a number of training examples. For SL, a training example usually consists of an event/entity and its corresponding ground-truth label. In classification, the ground-truth label indicates the class to which its associated event/entity belongs; in regression, the ground-truth label is a real-value response corresponding to the event/entity. There are two main streams in the current SL literature: fully supervised learning (FSL) and weakly supervised learning (WSL) [2]. FSL focuses on the situation where the training data set is assigned ideal (complete, exact and accurate) ground-truth labels. In contrast, WSL focuses on situations where the training dataset is assigned non-ideal (incomplete, inexact or inaccurate) ground-truth labels. The clear boundary between FSL and WSL is the properties (completeness, exactness and accuracy) of the ground-truth labels prepared for the training data set.

However, in many real practice FSL tasks, we cannot directly learn a predictive model that can map from events/entities in the training set to their corresponding ground-truth labels. The main reason for this situation lies in the fact that the given ground-truth labels are not always learnable though ideal are they. We must first construct a target transformation from the given ground-truth labels into structured learnable targets, then learn a predictive model that maps from events/entities in the training set to their corresponding learnable targets. Existing solutions for various FSL tasks have shown that the target transformation from the given ground-truth labels to the learnable targets can significantly affect the performance of the final FSL solution [3–7]. By referring to only the properties of the ground-truth labels prepared for the training data set without considering the properties of the target transformation, the roughness of the FSL category conceals some details that can be critical to building the optimal solutions for some specific FSL tasks. Thus, it is desirable to reveal these details. In the context of computer vision, this article attempts to achieve this goal by expanding the categorization of FSL and investigating the subtype that plays the central role in FSL.

Defining the properties of the target transformation for an FSL task into two types, ‘carelessly designed’ and ‘carefully designed’ (the definitions for ‘carelessly designed’ and ‘carefully designed’ can be found in Section 3.1), we further categorize FSL into three narrower subtypes. The three sub-types include precisely supervised learning (PSL), moderately supervised learning (MSL), and precisely and moderately combined supervised learning (PMCSL). PSL concerns the situation where the given ground-truth labels are precisely fine. In this situation, we are able to carefully design a target transformation to obtain the learnable targets from the given ground-truth labels. In other words, to some extent, the given ground-truth labels can be directly viewed as learnable targets. PSL is the most classic subtype of FSL, and typical tasks include simple tasks such as image classification [8] and complicated tasks such as image semantic segmentation [9]. MSL concerns the situation where the given ground-truth labels are ideal, but due to the simplicity in annotation of the given ground-truth labels, careful designs are required to transform the given ground-truth labels into learnable targets for the learning task. This situation is different from the classic PSL since the given ground-truth labels must be carefully transformed into learnable targets for the learning task, which would otherwise lead to poor performance. This situation is also different from WSL since the given ground-truth labels are not incomplete, inexact or inaccurate but ideal. We refer to this situation as an issue of moderately supervised learning (MSL) since the given ground-truth labels for the learning task are not as strong as for PSL or as weak as for WSL. Typical MSL tasks include cell detection (CD) [3] and line segment detection (LSD) [4]. PMCSL concerns the situation where the given ground-truth labels contain both precise and moderate annotations. Usually, PMCSL consists of a few PSL and MSL sub-tasks; thus, the target transformation for this situation requires both careless designs and careful designs. Typical PMCSL tasks include visual object detection [10], facial expression recognition [11] and human pose identification [12]. A short illustration of this narrower categorization is presented in Fig. 1, and more details can be found in Section 3.2.

In the three narrower sub-types, PSL only counts for a small proportion of FSL because simple tasks (such as image classification) of PSL are seldom and complicated tasks (such as image semantic segmentation) of PSL usually require precisely pixel-accurate ground-truth labels that are labour extensive. However, MSL is widely present in FSL because the ground-truth labels for MSL are simple in annotation and MSL is an essential part of PMCSL that accounts for the majority of FSL. As a result, MSL plays a central role in the field of FSL. Although solutions have been intermittently proposed for different MSL tasks, insufficient research has been devoted to elaborate MSL. In this paper, from the perspective of definition and framework, we comprehensively illustrate MSL, aiming to reveal what details are concealed by the roughness of the FSL category. We first formulate MSL to give it a clear definition, which proves that some details are indeed concealed by the roughness of the FSL category. Then, we present a generalized MSL framework, which reveals the key points of constructing fundamental MSL solutions and the key problems of developing better MSL solutions that are concealed by the roughness of the FSL category. Finally, discussions on the revealed details suggest that MSL should be given more attention.

2. Preliminary

Formally, a supervised learning (SL) task is to learn a function from a training data set \( \mathcal{T} \). Usually, \( d \) denotes a set of events/entities, \( g^* \) represents the given ground-truth labels corresponding to \( d \), and the training dataset \( \mathcal{T} \) consists of the events/entities \( d \) with their ground-truth labels \( g^* \). In the current literature, there are two main types of SL: FSL and WSL. Usually, these two types are distinguished according to the completeness, exactness and accuracy of the ground-truth labels prepared for the training data set \( \mathcal{T} \). Some basic notations that appear in this paper are summarized in Table 1.

| Type            | Description                                                                 |
|-----------------|-----------------------------------------------------------------------------|
| Fully supervised learning | FSL learns predictive models using complete, exact and accurate ground-truth labels. Specifically, the training data set \( \mathcal{T} = \{ (d_1, g_1^*), \ldots, (d_N, g_N^*) \} \), where \( N \) is the number of events/entities and each \( d_n \) has a label \( g_n^* \) that can ideally describe its ground truth. Based on such prepared training data sets, FSL has been widely adopted to solve many fundamental SL tasks, such as image classification, object tracking and detection, and image semantic segmentation in the field of computer vision [13–17]. |
| Weakly supervised learning | WSL attempts to learn predictive models with incomplete, inexact or inaccurate ground-truth labels [18]. Learning with incomplete ground-truth labels focuses on the situation where only a small amount of ideally labelled data is given to train a predictive model, while abundant unlabelled data are available. In this situation, the ideally labelled data are insufficient to learn a good |
Learning with inexact ground-truth labels concerns using only events/entities in the training data set; coloured ellipses indicate the ground-truth labels assigned to corresponding events/entities; coloured polygons signify learnable targets transformed from corresponding ground-truth labels.

**Fig. 1.** Narrower categorization for fully supervised learning (FSL). The three subtypes of FSL include precisely supervised learning (PSL), moderately supervised learning (MSL), and precisely and moderately combined supervised learning (PMCSL). Black rectangles denote events/entities in the training data set; coloured ellipses indicate the ground-truth labels assigned to corresponding events/entities; coloured polygons signify learnable targets transformed from corresponding ground-truth labels. \(<\approx/\approx\) denote 'carelessly designed'/'carefully designed' target transformation.

| Notation | Meaning |
|----------|---------|
| \(f\) | a function that maps from a to b |
| \(\mathcal{T}\) | a training data set that consists of events/entities with ground-truth labels |
| \(d\) | a set of events/entities |
| \(\mathbf{g}^*\) | Ground-truth labels corresponding to events/entities |
| \(N\) | number of events/entities in the training data set \(\mathcal{T}\) |
| \(\mathbf{t}^*\) | learnable targets, a transformation of \(\mathbf{g}^*\) |
| \(\leq\leq\leq\approx\) | non-parameterized/parameterized transformation |
| \(\Lambda/\Lambda\) | and/or |
| \(\mathbf{t}\) | predicted targets of events/entities |
| \(\mathbf{g}\) | final predicted labels, a re-transformation of \(\mathbf{t}^*\) |
| \(\mathbf{h}\) | space of learnable target \(\mathbf{g}\) |
| \(\mathbf{f}\) | space of predicted target \(\mathbf{t}\) |
| \(\mathbf{H}\) | space of final predicted labels \(\mathbf{g}\) |
| \(\omega^d/\omega^l/\omega^e\) | parameters for Decoder/Inferrer/Encoder |
| \(M^d/M^l/M^e\) | space of parameters for Decoder/Inferrer/Encoder |

**Table 1.** Summary of different works pertaining to face and speech fusion

---

The categorization of SL in the preliminary section simply takes into consideration the properties (completeness, exactness and accuracy) of the ground-truth labels prepared for the training data set. However, in practice, we usually cannot directly learn a function \(f: d \rightarrow \mathbf{g}^*\) for an FSL task. We must build a target transformation from given ground-truth labels \(\mathbf{g}^*\) to learnable targets \(\mathbf{t}^*\) and learn a function \(f: d \rightarrow \mathbf{t}^*\). In this section, by taking the properties of the target transformation from \(\mathbf{g}^*\) to \(\mathbf{t}^*\) into consideration, we expand the categorization for FSL. Usually, a target transformation for an FSL task is coupled with a label re-transformation from the predicted targets of the learned function \(f\) to the final predicted labels. Since a label re-transformation commonly consists of the reverse operations corresponding to its coupled target transformation, in this section, we assume that the properties of the label re-transformation remain the same as the multi-instance learning [21].

Specifically, the training data set \(\mathcal{T} = \{(d_1, g_1^*), \cdots, (d_N, g_N^*)\}\), where \(d_n = \{d_{n,1}, \cdots, d_{n,Mn}\} \subseteq d\) is called a bag, \(d_{nm} \in d\) (\(m \in \{1, \cdots, M_n\}\)) is an instance, and \(M_n\) is the number of instances in \(d_n\). For a two-class classification multi-instance learning task where \(t^* = \{y, n\}\), \(d_n\) is a positive bag, i.e., \(t^* = \{y\}\), if there exists \(d_{np}\) that is positive, while what is known is only \(p \in \{1, \cdots, M_n\}\). The goal is to predict labels for unseen bags. Learning with inaccurate ground-truth labels focuses on using data, the labels of which, compared with the ideal ground-truth labels, may contain errors to train a reasonable predictive model. A typical technique for this situation is learning with noisy labels [22].

Specifically, the training data set \(\mathcal{T} = \{(d_1, g_1^* + \Delta_1), \cdots, (d_N, g_N^* + \Delta_N)\}\), where \(g_n^* + \Delta_n\) is the given ground-truth label, which consists of an accurate label \(g_n^*\) and a label error \(\Delta_n\). With the efficiency and lower cost of the data labelling process, WSL has become popular for addressing many complicated SL tasks that require extensive labour annotations.

### 3. Narrower Subtypes of Fully Supervised Learning

The categorization of SL in the preliminary section simply takes into consideration the properties (completeness, exactness and accuracy) of the ground-truth labels prepared for the training data set. However, in practice, we usually cannot directly learn a function \(f: d \rightarrow \mathbf{g}^*\) for an FSL task. We must build a target transformation from given ground-truth labels \(\mathbf{g}^*\) to learnable targets \(\mathbf{t}^*\) and learn a function \(f: d \rightarrow \mathbf{t}^*\). In this section, by taking the properties of the target transformation from \(\mathbf{g}^*\) to \(\mathbf{t}^*\) into consideration, we expand the categorization for FSL. Usually, a target transformation for an FSL task is coupled with a label re-transformation from the predicted targets of the learned function \(f\) to the final predicted labels. Since a label re-transformation commonly consists of the reverse operations corresponding to its coupled target transformation, in this section, we assume that the properties of the label re-transformation remain the same as the multi-instance learning [21].
properties of its coupled target transformer and give no additional discussions.

3.1. Properties of target transformation

We classify the target transformations of solutions for FSL tasks into 'carelessly designed' and 'carefully designed' two types. On the basis of the intrinsic fact that a non-parameterized target transformation simply requires careless designs while a parameterized target transformation must requires careful designs, we define that a target transformation is the 'carelessly designed' type if it is non-parameterized, and a target transformation is the 'carefully designed' type if it is parameterized. That a non-parameterized target transformation simply requires careless designs is because the nonparameterized target transformation can only generate a single type of learnable target that can be considered to be optimal. However, a parameterized target transformation must require careful designs because adjusting the parameters of a parameterized target transformation can generate various types of learnable targets from which finding the optimal type of learnable targets is quite difficult. To formally summarize the properties of a target transformation, we present Definition 1 as follows.

Definition 1. For the given ground-truth labels \( g^* \), the learnable targets generated by a 'carelessly designed' transformation are

\[
t^* = \left\{ t^*_n \leq g^*_n, n \in \{1, \ldots, N\} \right\},
\]

where \( \leq \) signifies the non-parameterized transformation of \( t^*_n \) from \( g^*_n \) and the learnable targets generated by a 'carefully designed' transformation are

\[
t^* = \left\{ t^*_n \preceq g^*_n, n \in \{1, \ldots, N\} \right\},
\]

where \( \preceq \) signifies the parameterized transformation of \( t^*_n \) from \( g^*_n \).

3.2. Subtypes of FSL

Taking into consideration the two properties of a target transformation presented in Definition 1, we further classify FSL into three narrower subtypes: PSL, MSL, and PMCSL.

3.2.1 Precisely supervised learning

PSL concerns the situation where the given labels \( g^* \) in the training data set have precisely fine ground-truth labels. In this situation, we can simply construct a nonparameterized target transformation with careless designs to obtain the learnable targets \( t^* \) from \( g^* \). Image classification [8] and pixel-level accurate image semantic segmentation [9] are two typical PSL problems.

In a \( C \)-class image classification task, the given ground-truth label for the class of an image can usually be transformed into a learnable target using a \( C \)-bit vector. In this vector, the bit corresponding to the given ground-truth label is set to 1, and the remaining bits are set to 0. Similarly, for a \( C \)-class image semantic segmentation task, each pixel point in the given ground-truth label for the semantic objects in an image can be transformed into a value at the same pixel point in the learnable target. The transformed value can be a one-hot vector in classification or real-value response in regression, corresponding to its predefined class in the given ground-truth label. We can note that the target transformations for these two PSL tasks are non-parameterized and can be simply built with careless designs. In other words, to some extent, the given ground-truth labels \( g^* \) can be viewed as learnable targets due to their precise fineness.

3.2.2 Moderately supervised learning

MSL focuses on the situation where the given ground-truth labels \( g^* \) in the training dataset are ideal while possessing simplicity to some extent. This situation is different from PSL since the simplicity of \( g^* \) makes directly learning from the learnable targets of its carefully designed transformation probably impossible or leads to very poor performance. MSL is also different from WSL, as the given ground-truth labels are not incomplete, inexact or inaccurate but ideal. Since the given ground-truth labels are not strong enough for PSL but also not weak enough for WSL, we refer to this situation as MSL. Due to the simplicity of \( g^* \), in this situation, the target transformation from \( g^* \) to learnable targets \( t^* \) is usually parameterized and requires careful designs. Cell detection (CD) [3] and line segment detection (LSD) [4] are two typical MSL tasks.

In the CD task, the given ground-truth labels for cells in an image lattice are usually a set of 2D points indicating the cell centres. In the LSD task, the given ground-truth labels for line segments in an image lattice are simply a set of tuples, each of which contains two 2D points. The connection between the two 2D points of a tuple indicates a line segment in an image lattice. As the given ground-truth labels for these two tasks are simple, directly transforming them into learnable targets, in which pixel points corresponding to \( g^* \) are set as foreground objects and the rest are set as background objects, will make the learning task impossible or lead to very poor performance. A more appropriate target transformation that is restricted by a number of parameters (a parameterized target transformation) can be used to alleviate this situation. However, adjusting the parameters of this parameterized target transformation can result in various learnable targets that can significantly affect the performance of the final solution for an MSL task. As a result, it is usually difficult to find the optimal learnable targets from the parameterized target transformation for an MSL task. Thus, an appropriately parameterized target transformation for an MSL task must require careful designs to be constructed.

3.2.3 Precisely and moderately combined supervised learning

PMCSL concerns the situation where the given ground-truth labels \( g^* \) contain both precise and moderate annotations. In this situation, the target transformation is usually built to have a mixture of properties of both the target transformations designed for PSL and MSL tasks. Typical PMCSL tasks include visual object detection [10], facial expression recognition [11] and human pose identification [12]. Each of these tasks usually consists of a few PSL and MSL problems.

In the visual object detection task, the given ground-truth labels for the objects in an image lattice are usually a set of tuples, each containing a class name and a bounding box to indicate the category of an object and its position. Currently, deep convolutional neural network-based [8,23–27] one-stage approaches (YOLO [28–31], SSD [32] and RetinaNet [6]) and two-stage approaches (RCNN [33], SPPNet [34], Fast RCNN [35], Faster RCNN [36] and FPN [5]) are the state-of-the-art solutions for this task. The target transformations of these solutions usually have a parameterized sub-transformation and a non-parameterized sub-transformation. The parameterized sub-transformation is responsible for pre-defining a set of reference boxes (a.k.a. anchor boxes) with different sizes and aspect ratios at different locations of an image lattice. The sizes and aspect ratios can be adjusted to generate various reference boxes. These reference boxes are used to indicate the probabilities of corresponding areas as objects in an image lattice. The non-parameterized sub-transformation is responsible for transforming the reference boxes obtained from the parameterized sub-transformation into their categories and locations according to the ground-truth class names and ground-
truth bounding boxes labelled in an image lattice. In facial expression recognition [11] and human pose identification [12] tasks, the detection of landmarks of a face or a human is the primary problem. The given ground-truth labels for the landmarks of a face or a human in an image are usually a set of tuples, each of which contains a 2D vector and a number to indicate the position and category of the landmark. The target transformation of possible solutions for the detection of landmarks also has a parameterized sub-transformation and a non-parameterized sub-transformation. Basically, the detection of landmarks consists of two subproblems: locating the landmarks and classifying the located landmarks. The parameterized sub-transformation, which is similar to the target transformers of solutions for pure MSL located landmarks. The parameterized sub-transformation is responsible for producing targets for classifying the located landmarks. These typical problems show that the target transformation for PMCSL enjoys a mixture of properties of the target transformations for pure PSL and pure MSL.

3.3. Analysis

In fact, the three subtypes (PSL, MSL and PMCSL) of FSL can be converted between each other by changing the modelling methods of the target transformations for their solutions. However, once the target transformation for a possible solution has been constructed, the subtype of the corresponding FSL task is clearly clarified. In other words, the constructed target transformation of a possible solution for an FSL task fundamentally determines the subtype of this FSL task, which is crucial to building the appropriate solution for the task. Additionally, taking Definition 1 into consideration, WSL can also be classified into narrower subtypes. However, here, we only focus on the subtypes of FSL, since FSL is more fundamental than WSL in the field of SL and the subtypes of FSL can naturally adjust to WSL.

4. Moderately Supervised Learning: Definition and Framework

In the three narrower sub-types, PSL only counts for a small proportion of FSL because simple tasks (such as image classification) of PSL are seldom in FSL and complicated tasks (such as image semantic segmentation) of PSL usually require precisely pixel-accurate ground-truth labels that are labour extensive. However, MSL is widely present in FSL because the ground truth labels required by MSL are simple in annotation and MSL is also an essential part of PMCSL which counts for the majority of FSL. As a result, MSL plays a central role in the field of FSL. Currently, insufficient research has been devoted to comprehensively illustrating MSL, although solutions have been intermittently proposed for different MSL tasks. In this section, we comprehensively illustrate MSL from the perspective of the definition and framework, aiming to reveal the details concealed by the roughness of the FSL category.

4.1. Definition

4.1.1 Definition of FSL

Let us consider the situation where the given ground-truth labels of an amount of data are the ideal labels but possess simplicity. Specifically, with the given simple ground-truth labels $g^*$, the ultimate goal of the learning task here is to find the final predicted labels $g$ that minimize the error against $g^*$. Regarding this situation as a classic FSL problem, we can define the objective function as

$$\min_g \ell(g, g^*), \quad (0-1)$$

where $\ell(\cdot, \cdot)$ refers to a loss function that estimates the error between two given elements. The smaller the value of this function is, the better the found $g$ is.

4.1.2 Definition presented for MSL

Due to the simplicity of $g^*$, we must carefully build a target transformation that transforms $g^*$ into learnable targets $t^*$. On the basis of the transformed learnable targets $t^*$, we build a learning function that maps events/entities $t^*$ to the predicted targets and find those predicted targets $t$ that minimize the error against $t^*$. Based on the found predicted targets $t$, we then carefully build a label re-transformation that re-transforms $t$ into the final predicted labels and find those predicted labels $g$ that can minimize the error against the ground-truth labels $g^*$. We assume $t^*$ can be constructed by ‘decoding’ $g^*$ as the learnable targets $t^*$ are more informative than the ground-truth labels $g^*$, the predicted targets $t$ can be obtained by ‘inference’ $g^*$ and $g$ can be constructed by ‘encoding’ $t$ as the final predicted labels $g$ are less informative than the predicted targets $t$. Formally, we specify the following definitions for MSL:

$$t^* = \text{decoder}(g^*) \quad t^* \in I,$$

$$t = \text{inference}(d) \quad t \in J, \min_{t \in J} \ell(t, t^*),$$

$$g = \text{encoder}(t) \quad g \in H, \min_{g \in H} \ell(g, g^*) \quad (0-2)$$

where $\text{decoder}$ denotes the target transformation, $\text{inference}$ denotes the learning function, $\text{encoder}$ denotes the label re-transformation, and $I$, $J$ and $H$ denote the spaces of learnable targets $t^*$, predicted targets $t$ and final predicted labels $g$, respectively.

4.1.3 Analysis

Comparing Eq. (0-2) with Eq. (0-1), we can note that, by taking into consideration the properties of the target transformation from the given ground-truth labels to learnable targets, the definition presented for MSL proves that some details are indeed concealed by the rough definition for FSL.

4.2. Framework

On the basis of the specified definitions for MSL, we present a generalized MSL framework. The outline of the presented MSL framework is shown in Fig. 3, in which basic components for constructing a fundamental MSL solution and basic procedures of mutual collaborations among the basic components are depicted.

4.2.1 Basic component

The $\text{decoder}$ transforms the given simple ground-truth labels $g^*$ into learnable targets $t^*$. Commonly, the decoder is built on the basis of prior knowledge, which is parameterized by $\omega^d$. Abstractly, we obtain the learnable targets $t^*$ by

$$t^* = \text{decoder}(g^*; \omega^d). \quad (1)$$

The $\text{inference}$ models the map between the events/entities $d$ and corresponding learnable targets $t^*$. Usually, the $\text{inference}$ is built on the basis of machine learning techniques and is parameterized by $\omega^i$. Abstractly, we obtain the predicted targets $t$ by

$$t = \text{inference}(d; \omega^i). \quad (2)$$

The $\text{encoder}$ re-transforms the predicted targets $t$ of the $\text{inference}$ into the final predicted labels $g$. Coupled with the decoder, the $\text{encoder}$ is built on the basis of the decoder’s output $t^*$, which is parameterized by $\omega^e$. Abstractly, we obtain the final predicted labels $g$ by

$$g = \text{encoder}(t; \omega^e). \quad (3)$$
4.2.2 Basic procedure

**Learning** The learning procedure aims to optimize the parameters $\omega^I$ and $\omega^E$ for the inferrer and encoder, respectively, under the prerequisite of a decoder that is empirically initialized with $\omega^D_*$. Specifically, we express the learning procedure as

\[ t^i = \text{inferrer}(d; \omega^I, t^*_n), \quad (6-1) \]

\[ \omega^I_* = \arg \min_{\omega^I \in \mathbb{M}^I} \frac{1}{N} \sum_{n=1}^{N} L^I(\text{inferrer}(d_n; \omega^I), t^*_{n}), \quad (4-2) \]

\[ \omega^E_* = \arg \min_{\omega^E \in \mathbb{M}^E} \frac{1}{N} \sum_{n=1}^{N} L^E(\text{encoder}(t_n; \omega^E), g^*_{n}), \quad (4-3) \]

where $\mathbb{M}^I$ and $\mathbb{M}^E$ specify the parameter spaces of $\omega^I$ and $\omega^E$, respectively, and $N$ is the number of training events/entities.

**Looping** As the optimization of the parameters ($\omega^I, \omega^E$) of both the inferrer and encoder is conducted under the prerequisite of the decoder parameterized by $\omega^D$, a change in the decoder can significantly affect the optimization of $\omega^I$ and $\omega^E$, which will eventually be reflected in the final predicted labels $g$. In fact, prior knowledge can be enriched by analysing the predicted labels $g$ of the current solution. The enriched prior knowledge can help us to model and initialize a better decoder. Thus, in practice, we can loop several times to adjust the decoder and restart the training for a possibly better solution. Specifically, we express the looping procedure as

\[ \omega^{D_*} = \min_{\omega^D \in \mathbb{M}^D} L(g|\omega^D, g^*), \quad (5) \]

where $\mathbb{M}^D$ signifies the parameter space of $\omega^D$ and $g|\omega^D$ denotes the final predicted labels obtained by optimizing the parameters ($\omega^I, \omega^E$) of both the inferrer and encoder under the prerequisite of the decoder initialized with $\omega^D$.

**Testing** As shown in Fig. 2, testing starts from input $d$, passes through the inferrer and encoder, and ends at $g$. Specifically, the testing procedure can be expressed as

\[ t = \text{inferrer}(d; \omega^I, t^{d_*}), \quad (6-1) \]

\[ g = \text{encoder}(t; \omega^E, \omega^D_*), \quad (6-2) \]

where $\omega^{I_*}|\omega^{d_*}$ and $\omega^{E_*}|\omega^{d_*}$ are the parameters of the inferrer and encoder optimized under the prerequisite of the decoder initialized with $\omega^{d_*}$ found by the looping procedure.

4.2.3 Analysis

From Eq. (1) to (6), we can note that the generalized framework presented for MSL reveals the key points of constructing fundamental MSL solutions and the key problems of developing better MSL solutions that are concealed by the roughness of the FSL category. The key points of constructing fundamental MSL solutions can be summarized as modelling the three basic components (decoder, inferrer and encoder), and the key problems of developing better MSL solutions can be summarized as the learning and looping procedures to optimize the three basic components. The decoder is responsible for transforming the given ground-truth labels into learnable targets. Usually, it is built and optimized on the basis of prior knowledge. The inferrer is responsible for mapping events/entities to corresponding learnable targets. Usually, it is built and optimized on the basis of machine learning techniques. The encoder is responsible for transforming the predicted targets of the inferrer into final predicted labels. Usually, the encoder is built and optimized on the basis of the decoder.

5. Discussion

By simply referring to the properties of the ground-truth labels prepared for the training data set, in the current literature, SL is roughly categorized as FSL and WSL. However, the roughness of the FSL category conceals some details that can be critical to building the optimal solutions for some specific FSL tasks. In the context of computer vision, this article attempts to reveal the concealed details by expanding the categorization of FSL and investigating the subtype that plays the central role in FSL. Taking into consideration the properties of the target transformation from the given ground-truth labels to learnable targets, we first categorize FSL into three narrower subtypes. Then, we focus on the subtype MSL that plays the central role in FSL. From the perspective of the definition and framework, we comprehensively illustrate MSL to reveal what details are concealed by the roughness of the FSL category. The revealed details include the key points of constructing fundamental MSL solutions and the key problems of developing better MSL solutions. More specifically, the key points of constructing fundamental MSL solutions are to

- model the three basic components (decoder, inferrer and encoder),
- and the key problems of developing better MSL solutions are to optimize the three basic components.

Under the background of the popularization of big data, computing resources and deep learning technology (especially DCNNs from complex \cite{8,23–27} to lightweight \cite{37–39}), modelling and optimising the inferrer to map events/entities to their corresponding learnable targets has become increasingly standardized. Abundant modelling approaches \cite{40–43} and optimization methods \cite{44,45} have been proposed for the inferrer, while the modelling and optimization of the decoder and the encoder lack systematic and comprehensive studies, except for some sporadic solutions for specific MSL tasks \cite{3–6}. Primarily, modelling an appropriate decoder is especially important, as it determines how an MSL task is defined and is the prerequisite for optimizing both the inferrer and decoder. Thus, it is valuable to investigate how to effectively model a decoder for an MSL task with prior knowledge. Additionally, the decoder for a typical MSL task is usually parameterized, and optimizing its parameters usually requires a tedious looping procedure. As the optimization for both the inferrer and encoder is conducted under the prerequisite of the decoder, if the parameters of the decoder are changed, both the inferrer and encoder must be reoptimized. Thus, how to efficiently and effectively optimize the parameters of the decoder is a problem worth studying. Last, because it is coupled
with the decoder, small changes in the encoder can also significantly affect the final performance [3, 4]. Thus, it would also be interesting to investigate how to find an appropriate decoder for an MSL task. Respectively being the preprocessing and postprocessing for the inferer, the decoder and the encoder are both critical to building better MSL solutions, especially when the machine learning technique based inferer is reaching its limits. These discussions, in summary, suggest that MSL should be given more attention.

Acknowledgements

This work was supported by the Sichuan Science and Technology Program (2020YFS0088); the 1·3·5 project for disciplines of excellence Clinical Research Incubation Project, West China Hospital, Sichuan University (2019HXFH036); the National Key Research and Development Program (2017YFC0113908), China; the Technological Innovation Project of Chengdu New Industrial Technology Research Institute (2017-CY02-00026-GX).

References

[1] Y. LeCun, Y. Bengio, G. Hinton, Deep learning, Nature. 521 (2015) 436-444. doi:10.1038/nature14539.
[2] Z.-H. Zhou, A brief introduction to weakly supervised learning, Natl. Sci. Rev. 5 (2018) 44–53. doi:10.1093/nsr/nwx106.
[3] Y. Xie, F. Xing, X. Shi, X. Kong, H. Su, L. Yang, Efficient and robust cell detection: A structured regression approach, Med. Image Anal. 44 (2018) 245–254. doi:10.1016/j.media.2017.07.003.
[4] N. Xue, S. Bai, F.-D. Wang, G.-S. Xia, T. Wu, L. Zhang, P.H.S. Torr, Learning Regional Attraction for Line Segment Detection, IEEE Trans. Pattern Anal. Mach. Intell. (2019). doi:10.1109/tpami.2019.2958642.
[5] T.Y. Lin, P. Dollár, R. Girshick, K. He, B. Hariharan, S. Belongie, Feature pyramid networks for object detection, in: Proc. - 30th IEEE Conf. Comput. Vis. Pattern Recognition, CVPR 2017, 2017. doi:10.1109/CVPR.2017.106.
[6] T.Y. Lin, P. Goyal, R. Girshick, K. He, P. Dollar, Focal Loss for Dense Object Detection, IEEE Trans. Pattern Anal. Mach. Intell. (2017). doi:10.1109/TPAMI.2018.2858826.
[7] H. Law, J. Deng, CornerNet: Detecting Objects as Paired Keypoints, Int. J. Comput. Vis. (2020). doi:10.1007/s11263-019-00220-4.
[8] A. Krizhevsky, I. Sutskever, G.E. Hinton, ImageNet Classification with Deep Convolutional Neural Networks, in: Adv. Neural Inf. Process. Syst., 2012: pp. 1097–1105.
[9] S. Ghosh, N. Das, I. Das, U. Maulik, Understanding deep learning techniques for image segmentation, ACM Comput. Surv. (2019). doi:10.1145/3329784.
[10] Z.Q. Zhao, P. Zheng, S.T. Xu, Y. Wu, J. Sun, Deep Residual Learning for Image Recognition, in: 2016 IEEE Conf. Comput. Vis. Pattern Recognition, IEEE, 2016: pp. 770–778. doi:10.1109/CVPR.2016.90.
[11] J. Redmon, S. Divvala, R. Girshick, A. Farhadi, You only look once: Unified, real-time object detection, in: Proc. IEEE Conf. Soc. Comput. Vis. Pattern Recognition., 2016. doi:10.1109/CVPR.2016.91.
[12] J. Redmon, A. Farhadi, YOLO9000: Better, faster, stronger, in: Proc. - 30th IEEE Conf. Comput. Vis. Pattern Recognition, CVPR 2017, 2017. doi:10.1109/CVPR.2017.690.
[13] J. Redmon, A. Farhadi, Youv3, Proc. IEEE Conf. Soc. Comput. Vis. Pattern Recognition., 2017. doi:10.1109/CVPR.2017.690.
[14] R. Girshick, J. Donahue, T. Darrell, J. Malik, Rich feature hierarchies for accurate object detection and semantic segmentation, in: Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognition., 2014. doi:10.1109/CVPR.2014.81.
[15] K. He, X. Zhang, S. Ren, J. Sun, Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition, IEEE Trans. Pattern Anal. Mach. Intell. (2015). doi:10.1109/TPAMI.2015.2389824.
[16] R. Girshick, Fast R-CNN, in: Proc. IEEE Int. Conf. Comput. Vis., 2015. doi:10.1109/ICCV.2015.169.
[17] S. Ren, K. He, R. Girshick, J. Sun, Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks, IEEE Trans. Pattern Anal. Mach. Intell. (2017). doi:10.1109/TPAMI.2016.2577031.
[18] A. Howard, M. Sandler, B. Chen, W. Wang, L.C. Chen, M. Tan, G. Chu, V. Vasudevan, Y. Zhu, R. Pang, Q. Le, H. Adam, Searching for MobileNetV3, in: Proc. IEEE Int. Conf. Comput. Vis., 2019. doi:10.1109/ICCV.2019.00140.
[19] K. Sun, M. Li, D. Liu, J. Wang, IGCv3: Interleaved low-rank group convolutions for efficient deep neural networks, in: Br. Mach. Vis. Conf. 2018, BMVC 2018, 2019.
[20] X. Zhang, H. Zheng, J. Sun, ShuffleNetV2, ECCV. (2018).
[21] E. Shelhamer, J. Long, T. Darrell, Fully Convolutional Networks for Semantic Segmentation, IEEE Trans. Pattern Anal. Mach. Intell. 39 (2017) 640–651. doi:10.1109/TPAMI.2016.2572683.
[22] V. Badrinarayanan, A. Kendall, R. Cipolla, SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation, IEEE Trans. Pattern Anal. Mach. Intell. 39 (2017) 2481–2495. doi:10.1109/TPAMI.2016.2644615.
[23] L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, A.L. Yuille, Semantic Image Segmentation with Deep Convolutional Nets, Arxiv, and Fully Connected CRFs, IEEE Trans. Pattern Anal. Mach. Intell. 40 (2018) 834–848. doi:10.1109/TPAMI.2017.2699184.
[24] T. Falk, D. Mai, R. Bensch, Ó. Çiçek, A. Abdulkadir, Y. Marrakchi, A. Böhm, J. Deubner, Z. Jäckel, K. Seiwald, A. Dovzhenko, O. Tietz, C. Dal Bosco, S. Walsh, D. Saltukoglu, L.T. Tay, M. Prinz, K. Palme, M. Simons, I. Pfeifer, T. Brox, O. Ronneberger, U-Net: deep learning for cell counting, detection, and morphometry, Nat. Methods. (2019). doi:10.1038/s41592-018-0261-2.
[25] L. Bottou, Large-Scale Machine Learning with Stochastic Gradient Descent, in: Proc. COMPSTAT 2010, 2010. doi:10.1007/978-3-7908-2604-3.
[26] J. Duchi, E. Hazan, Y. Singer, Adaptive subgradient methods for online learning and stochastic optimization, J. Mach. Learn. Res. (2011).