AN EMPIRICAL EVALUATION OF MULTI-TASK LEARNING IN DEEP NEURAL NETWORKS FOR NATURAL LANGUAGE PROCESSING

Jianquan Li, Xiaokang Liu
Beijing Ultrapower Software Co., Ltd
{lijianquan2, liuxiaokang1}@ultrapower.com.cn

Wenpeng Yin
Department of Computer and Information Science, University of Pennsylvania
wenpeng@cis.lmu.de

Min Yang
Shenzhen Institutes of Advanced Technology (SIAT), Chinese Academy of Sciences
min.yang@siat.ac.cn

Liqun Ma
Beijing Ultrapower Software Co., Ltd
maliqun@ultrapower.com.cn

ABSTRACT
Multi-Task Learning (MTL) aims at boosting the overall performance of each individual task by leveraging useful information contained in multiple related tasks. It has shown great success in natural language processing (NLP). Currently, a number of MTL architectures and learning mechanisms have been proposed for various NLP tasks. However, there is no systematic exploration and comparison of different MTL architectures and learning mechanisms for their strong performance in-depth. In this paper, we conduct a thorough examination of typical MTL methods on a broad range of representative NLP tasks. Our primary goal is to understand the merits and demerits of existing MTL methods in NLP tasks, thus devising new hybrid architectures intended to combine their strengths.

1 Introduction
Multi-Task Learning (MTL) with deep neural networks have recently shown promising results in many NLP tasks, especially when there is no sufficient training data. The main idea of MTL is to leverage useful information contained in multiple related tasks to improve the generalization performance of all the tasks [30]. Generally, existing MTL methods with deep neural networks can be divided into two primary categories: hard parameter sharing and soft parameter sharing. Hard parameters sharing is the most common used MTL framework, which shares the hidden layers among all tasks but each task has its specific output layer [11, 29, 13]. While for soft parameters sharing, each task has its own neural network architecture with specific parameters. Information is passed by skip connections between the architecture for each task [16, 27].

In particular, we tease apart the typical hard and soft parameter sharing MTL methods in deep neural networks into six categories: gate mechanism [16, 27], simple hard parameters sharing [11, 29, 13], exploring linguistic hierarchies [23, 8], adversarial learning [12], orthogonality constraint [20, 2], and label embedding [1]. We describe these six MTL methods in detail in Section 5.
Most previous MTL methods have declared state-of-the-art results for specific tasks. However, they are carefully designed and evaluated on selected (often one or two) datasets that can demonstrate the superiority of the model. This raises the scientific questions of whether the successes of these MTL approaches are confined to specific tasks and how much performance gain is due to certain architecture designs rather than hyperparameter optimizations.

To address these questions and understand different MTL architectures in-depth, we conduct systematically empirical evaluation of the widely used MTL architectures with deep neural networks on a broad range of NLP tasks, including text classification, semantic textual similarity, natural language inference, question answering, part-of-speech tagging, and chunking. By identifying the essential MTL architecture designs that contribute significantly to the success of MTL, we propose a hybrid architecture built with different components borrowed from previous MTL methods. For fair comparison, we merely retain the base structure of each MTL architecture and remove the training tricks in the original works.

To the best of our knowledge, we are the first to conduct a thorough examination of existing MTL methods on various NLP tasks and present a series of findings with quantitative measurements and in-depth analysis:

- All six individual MTL methods contribute great improvements to the overall performance on the six benchmark datasets.
- Using linguistic hierarchical information performs better than other individual MTL methods.
- Combining gate mechanism, label embedding and hard parameters sharing with linguistic hierarchies can achieve best results on a broad range of NLP tasks.

2 Related Work

Multi-task learning with deep neural networks has gained increasing attention within NLP community over the past decades. [18] and [30] described most of the existing techniques for multi-task learning in deep neural networks. Generally, existing MTL methods can be categorised as soft parameter sharing [16, 27] and hard parameter sharing [29, 13].

For soft parameter sharing, [7] use the L2 distance between (selective parts of) the main and auxiliary models to regularize parameters. Analogously, [28] use the trace norm for regularization. However, regularization can not autonomously choose which information to share. So, [16] and [27] respectively proposed cross-stitch unit and gate sharing unite to learn shared representations in neural network.

Hard parameters sharing without extra learning technology of MLT is widely used. [11] and [29] utilize simple hard parameters sharing structure to jointly learning multi-domain text classification tasks and different sequence-tagging tasks across languages respectively. And [13] use the pre-trained BERT as shared layers and obtain new state-of-the-art results on ten NLU tasks. Visibly, the feature learned by hard parameter sharing divide into private and share feature space. [20] and [2] argued that private feature space and share feature space may be mixed with each other and results in the reduction of model’s performance. So, they proposed orthogonality constraints to alleviate this issue. [12]proposed adversarial training framework for the same sake. In addition, [23] and [8] introduced the information of linguistic hierarchies into share feature space by predicting increasingly complex NLP tasks at successively deeper share layers.

The methods mentioned above do not consider the information of tasks’ label, so [1] proposes to induce a joint label embedding space using a label embedding layer that can model relationships between different NLP task and discovered it is effective for MTL.

3 Problem Definition

We assume that there are T tasks for multi-task learning, denoted as $T_1, T_2, \ldots, T_T$. The training data of each task is represented as $D^{Tk}$, where $k \in \{1, 2, \ldots, T\}$. Let $L_{Tk}(D^{Tk}, \Omega)$ stands for the loss function of task $T_k$, where $\Omega$ donates the total parameters in MTL model. The aim of MTL is finding $\Omega^*$ which accords with following equation:

$$
\Omega^* = \arg\min_{\Omega} \sum_{k=1}^{T} \lambda^{Tk} L_{Tk}(D^{Tk}, \Omega)
$$

(1)

where $\lambda^{Tk}$ is the weight for task $T_k$. 

The instance of train data in $D^T_k$ is noted as $(x^T_k, y^T_k)$, where $x^T_k = (x^T_{k1}, \ldots, x^T_{kl_k})$, $x^T_k \in \mathbb{R}^e$ is a $e$-dimensional word embedding of $i$-th word in the $T_k$-th task’s sentence and $y^T_k = \{y^T_{k1}, y^T_{k2}, \ldots, y^T_{kN^T_k}\}$ is the corresponding ground-truth label, $N^T_k$ is the number of class categories for task $T_k$, $l_k$ is the length of the sentence.

4 Basic MTL Architecture

In order to experiment easily with different MTL methods, we define an MTL framework which contains several combinable and nestable blocks, as illustrated in Figure 1. Next, we will elaborate on this framework in detail.

![Figure 1: Our experiment framework with out label embedding. Different color blocks represent different disassembled block in the experiment framework.](image)

4.1 Document Encoder Layer

We employ bidirectional long short-term memory network (BiLSTM) as the basic cell of our framework to encode the feature from input data. BiLSTM runs two LSTMs in both forward and backward directions on a sequence respectively. Therefore, for each word in a given sentence, BiLSTM can extract information about all words before and after it.

4.2 Shared Part

The whole MTL framework can divide into shared part and private part roughly. Shared part is composed of M-layer BiLSTMs that are shared by all tasks. Formally, the hidden state of each BiLSTM layer at step $i$ is calculated by:

$$s^T_{i,n} = BiLSTM(x^T_{i,n}, s^T_{i-1,n})$$  (2)
where \(s_{i}^{Tk,n} \in \mathbb{R}^{2l_{h}}\) is the \(i\)-th output vector in \(n\)-th layer of task \(T_k\)’s input sentence, \(n \in \{1, 2, \ldots, M\}\). And \(\tilde{s}_{i}^{Tk} = [x_{i}^{Tk}; s_{i}^{Tk,1}; s_{i}^{Tk,2}; \ldots; s_{i}^{Tk,n-1}]\). In our experiments, \(M = 3\).

### 4.3 Private Part

Each task has its own task-specific structures, each of which is composed of private feature extractor, pooling layer, and output layer.

**Private Feature Extractor** Private Feature Extractor aims at extracting the task-specific features of each task’s data. Here, it is a 1-layer BiLSTM for single sentence modeling. The hidden state of each BiLSTM layer at step \(i\) is calculated by:

\[
p_{i}^{Tk} = \text{BiLSTM}(x_{i}^{Tk}, p_{i-1}^{Tk})
\]

where \(p_{i}^{Tk} \in \mathbb{R}^{2l_{h}}\) is the \(i\)-th private hidden state in the given sentence for task \(T_k\). And it is a 2-layer BiLSTMs with soft alignment attention between BiLSTMs are adopted for sentence pair modeling.

**Pooling** We convert the learned feature vectors \(p_{i}^{Tk}\) to a fixed-length vector using pooling operation. Here, we adopt max and mean pooling operations:

\[
v_{mean}^{Tk} = \frac{1}{l_{sen}} \sum_{i=1}^{l_{sen}} p_{i}^{Tk}, \quad v_{max}^{Tk} = \max_{i=1}^{l_{sen}} p_{i}^{Tk}
\]

\[
v^{Tk} = [v_{mean}^{Tk}; v_{max}^{Tk}]
\]

where \(v^{Tk} \in \mathbb{R}^{4l_{h}}\) is the final sentence embedding for task \(T_k\)-th. The content of \(\tilde{p}_{i}^{Tk}\) is depended on the method we choose. When we adopt shared part, \(\tilde{p}_{i}^{Tk} = [p_{i}^{Tk}; s_{i}^{Tk,1}; s_{i}^{Tk,2}; s_{i}^{Tk,3}]\). When we remove shared part, \(\tilde{p}_{i}^{Tk} = p_{i}^{Tk}\). It is noteworthy that the private feature extractor and pooling could be removed in the framework, which is depended on the MTL method we choose.

**Output Layer** Output layer is a fully-connected neural network with softmax, which outputs the probability distribution of corresponding labels:

\[
\hat{y}^{Tk} = \text{softmax}(W_{k}v^{Tk} + b_{k})
\]

where \(W_{k}\) is a learnable parameter for \(T_k\), \(\hat{y}^{Tk} \in \mathbb{R}^{N_{Tk}}\). Finally, we can define the loss \(L_{task}\) as:

\[
L_{task} = \sum_{t=1}^{T} \lambda^{Tk} L_{Tk}
\]

where \(L_{Tk}\) is the loss function of task \(T_k\) and \(\lambda^{Tk}\) is the weight for task \(T_k\).

### 5 Different MTL Mechanisms

In this section, we describe the six MTL methods in detail.

#### 5.1 Simple Hard Parameters Sharing (SHPS)

Hard parameters sharing without other MTL learning technology is a widely used MTL method in deep neural networks. In this method, the input data of each task is transmitted to the shared part to obtain shared feature \(s_{i}^{Tk,n}\) using Eq.2. Then shared features are then transmitted to the corresponding private part to obtain final features with Eq.3-Eq.7.

#### 5.2 Exploring Linguistic Hierarchies (ELH)

[23] and [8] introduced the joint many-task model, which considers the linguistic hierarchies by predicting increasingly complex NLP tasks at successively deeper layers. In this study, we assume that this method uses three BiLSTM layers to handle three different fundamental tasks in the order of POS tagging, chunking, dependency parsing by considering linguistic hierarchies, rather than handling different tasks in the same abstractive layer. Note that this method should be used together with simple hard parameters sharing method. In the experiments, we define the final
loss function as the linear combination of the loss functions of POS tagging, chunking, dependency parsing, and the primary task:
\[
L_{lh} = L_{task} + L_{pos} + L_{chunk} + L_{parse}
\] (8)

### 5.3 Orthogonality Constraints (OC)

[2][2] proposed to factorize the latent space into shared and private spaces by introducing orthogonality constraints (OC), which penalize redundant latent representations. The orthogonality constraints are encoded as minimizing the Frobenius norm of the inner product between the private and shared representations. Formally, similar to [12], the orthogonality constraints are implemented by minimizing:
\[
L_{OC} = \lambda_{OC} \sum_{i=1}^{M} \sum_{n=1}^{T} ||(S_{Ti,n}^T P_{Ti})||_F^2
\] (9)

where, \(M\) is the number of LSTM layers in shared part. \(\lambda_{OC}\) is loss weight. \(||\cdot||_F\) is the Frobenius norm. \(S_{Ti,n}^T\) and \(P_{Ti}\) are two matrices, whose rows are the output of shared part and private feature extractor of an input sentence.

### 5.4 Adversarial Learning (AL)

To prevent the shared and private latent feature spaces from interfering with each other, [12][12] proposed an adversarial learning (AL) framework for multi-task learning, in which the adversarial training is used to encourage the shared features merely to contain task-invariant information. Specifically, an extra task adversarial loss \(L_{adv}\) is employed to encourage the model to produce shared features such that a task discriminator cannot reliably predict the task based on these features.

Formally, we use a discriminator \(D\) to output a probability distribution of based on the shared sentence representations, which estimates which task the encoded sentence comes from:
\[
D(s_k^T, \theta_D) = \text{softmax}(W_D s_k^T + b_D)
\] (10)

where \(W_D\) is a learnable parameter, \(b_D \in \mathbb{R}^{T}\) is a bias term, \(\theta_D\) denotes the parameters in discriminator.

Given a sentence, the adversarial loss is proposed to force the shared BiLSTMs to generate a representation to mislead the task discriminator \(D\). Following [12], the adversarial loss is extended to multi-class form, which allows the model can be trained together with multiple tasks:
\[
L_{adv} = \lambda_{adv} \min_{\theta_S} (\lambda_{max} \max_{\theta_D} \sum_{k=1}^{T} d_{Tk} \log[D(s_k^T, \beta)])
\] (11)

where \(\lambda_{adv}\) denotes the adversarial loss weight, \(d_{Tk}\) denotes the ground-truth label indicating the type of the current task, \(\theta_S\) denotes the parameters in shared part.

### 5.5 Gate Mechanism (Gate)

For soft parameter sharing, adding weighted futures learned by other tasks is a common way to share information among tasks [27][16][19], in which the weights of the features are learnable parameters. In this paper, we conclude these different weight learning mechanisms as gate mechanism (GM).

When investigating the effectiveness of the gate mechanism, we remove the shared part from the overall MTL framework, since the gate mechanism can learn to filter the feature flows between tasks and reduce the interference. Without loss of generality, we only consider two tasks: \(T_m\) and \(T_n\) in our multi-task learning framework for the sake of illustrating the gate mechanism concisely. We can generalize the model to the case of multiple tasks easily. As shown in Figure[1], each task has two gate units that learn the weights of the two kinds of features:
\[
g_1^T = \sigma(W_{g1} \hat{p}_n^T + b_{g1})
\] (12)
\[
g_2^T = \sigma(W_{g2} v_n^T + b_{g2})
\] (13)

\(\hat{p}_m^T\) and \(v_m^T\) can be updated by:
\[
\hat{p}_m^T = g_1^T \odot \hat{p}_n^T + \hat{p}_m^T
\] (14)
\[
v_m^T = g_1^T \odot v_n^T + v_m^T
\] (15)

where \(\odot\) denotes element-wise multiplication.
5.6 Label Embedding (LE)

For many NLP tasks, disparate label sets are weakly correlated, thus propose to induce a joint label embedding space using a Label Embedding (LE) layer that can model relationships between different NLP tasks. In particular, the output of each task $T_k$ and the loss $L_{task}$ are respectively calculated by:

$$\hat{z}^{T_k} = \text{softmax}(W_L v^{T_k} + b_L)$$

$$L_{task} = \sum_{k=1}^{T} \lambda^{T_k} \sum_{i=1}^{N} z^{T_k}_i \log(\hat{z}^{T_k}_i)$$

where $\hat{z}^{T_k} \in \mathbb{R}^N$. $N = \sum_{k=1}^{T} N^{T_k}$. $W_L$ is a learnable parameter and it is shared by all tasks. $z^{T_k} \in \mathbb{R}^N$ is the extension of $y^{T_k}$. Different task’s label is corresponding with the different part in the vector and the part does not belong to the task is padded with 0.

6 Experimental Setup

In order to systematically compare the effect of each MTL method, we conduct extensive experiments on three representative NLP tasks: text classification, text similarity, and textual inference. Each task contains two benchmark datasets. For fair comparison, in our experiments, we retain the base structure of the six methods and remove all training tricks and extra structures in original works.

6.1 Our Tasks and Datasets

We use the following datasets for our experiments. Table 1 shows the statistics of these datasets.

| Dataset | Training data | Testing data |
|---------|---------------|--------------|
| CoLA    | 8550          | 1042         |
| SST-2   | 67349         | 872          |
| MRPC    | 3668          | 408          |
| STS-B   | 5749          | 1500         |
| MNLI    | 392702        | 9815         |
| QNLI    | 108436        | 5732         |

Table 1: Statistics of the six experimental datasets.

Text Classification We use the Corpus of Linguistic Acceptability (CoLA) and Stanford Sentiment Treebank (SST-2) datasets to investigate the effectiveness of the MTL methods for text classification task. CoLA predicts whether an English sentence is linguistically acceptable or not. It uses Matthews correlation coefficient as the evaluation metric. SST-2 predicts whether the sentiment of sentences is positive or negative. Accuracy is used as the evaluation metric.

Text Similarity We use the Microsoft Research Paraphrase Corpus (MRPC) and Semantic Textual Similarity Benchmark STS-B for text similarity task. MRPC consists of sentence pairs with human annotations denoting whether a sentence pair is semantically equivalent to the other in the pair. Accuracy is used as evaluation metric. STS-B is a collection of sentence pairs which are manually annotated with similarity scores from one to five, indicating how similar the two sentences are. The evaluation metric is the Pearson and Spearman correlation coefficients.

Textual Inference We conduct experiments for textual inference task on Multi-Genre Natural Language Inference (MNLI) and Question-answering NLI (QNLI) datasets. MNLI contains large-scale, crowd-sourced premise-hypothesis pairs for textual entailment (TE). Each premise-hypothesis pair is labeled with a relation (i.e., entailment, contradiction, or neutral). The evaluation metric is accuracy. QNLI derived from the Stanford Question Answering Dataset, which has been converted to a binary classification task in GLUE. QNLI consists of query-candidate-answer tuples, each of which is labeled as positive or negative to indicate whether the given tuple contains the correct answer to the query. The evaluation metric is accuracy.

6.2 Basic Tasks and Datasets

For the method of exploring linguistic hierarchies, the shared 3-layer BiLSTMs also handle the three different basic tasks in the order of POS tagging, chunking, and dependency parsing respectively.
POS & Chunking  We use CoNLL-2003 [21] dataset (English part) for the POS and chunking tasks. In CoNLL-2003, each word is labeled with three kinds of tags: part-of-speech tag, chunk tag and named entity tag. The evaluation metric for POS and chunking is word-level accuracy.

Dependency Parsing (DP)  We use the Wall Street Journal (WSJ) part of the Penn Treebank [14] for dependency parsing, following the standard data split [5]. Specifically, we use Sections 2-21 for training, Section 22 for testing. The evaluation metrics are the Unlabeled Attachment Score (UAS).

6.3 Hyperparameters Setting

We use 300-dimensional pre-trained GloVe vectors[1] to initialize the word embeddings. The out-of-vocabulary (OOV) words are randomly initialized with a normal distribution with zero mean and one variance. Due to the unbalanced dataset size, the weight of each task in the joint loss function is calculated by the ratio of this data set size to the largest data set size.

For all task, we set the hidden state of all LSTMs to 300 dimensions, and the global dropout rate is set to 0.5. The other hyperparameters (e.g., learning rate, maximal sentence, minibatch size) are tuned on the validation data.

For dependency parsing task when exploring linguistic hierarchies, we set the dimensions of the two MLP layers as 50 and 100 respectively, similar to [10]. We set $\lambda_{adv} = 0.05$ and $\lambda_{OC} = 0.01$.

7 Experimental Results and Analysis

7.1 Single-task vs. Multi-task Analysis

We analyze the effectiveness of single-task and multi-task methods in detail and conduct an in-depth analysis of the experimental results. For the single-task method, we use the architecture introduced in Section 4, in which 1-layer BiLSTM is used for single sentence modeling and 2-layer BiLSTMs with attention are employed for sentence pair modeling. For the multi-task method, we first report the results of the individual MTL tasks on the six benchmarks. In addition, we combine the advances of these MTL methods to form an ensemble model (called ENS).

The results are summarized in Table 2. Generally, all six MTL methods contribute great improvements to the overall performance, and the ensemble model has the best comprehensive performance over all datasets. We have the following findings for the six MTL methods:

|        | SST | CoLA | MNLI | MRPC | QNLI | STS-B | POS | CHUNK | DP |
|--------|-----|------|------|------|------|-------|-----|-------|----|
| Single | 86.35 | 69.19 | 69.13 | 72.3 | 70.83 | 67.68 | 92.44 | 93.62 | 91.96 |
| SHPS   | 88.33 | 69.43 | 71.98 | 75.8 | 71.5 | 73.02 | n/a | n/a | n/a |
| ELH    | 89.45 | 70.06 | 72.1 | 79.78 | 73.44 | 71.49 | 94.2 | 95.75 | 96.64 |
| Gate   | 87.21 | 69.48 | 69.88 | 72.85 | 71.51 | 69.25 | n/a | n/a | n/a |
| LE     | 87.27 | 69.58 | 69.51 | 75 | 70.08 | 71.1 | n/a | n/a | n/a |
| OC*    | 88.13 | 69.1 | 70.94 | 73.29 | 71.77 | 65.71 | n/a | n/a | n/a |
| AL*    | 88.19 | 69.53 | 71.85 | 75.99 | 71.29 | 72.68 | n/a | n/a | n/a |
| ENS    | 88.42 | 69.48 | 72.43 | 80.15 | 74.48 | 69.18 | 94.12 | 95.66 | 96.65 |

Table 2: Single method result. Share stands for simple hard parameters sharing. ELH stands for exploring linguistic hierarchies. LE stands for label embedding. AL* stands for adversarial learning. OC* stands for orthogonality constraints.

Simple hard parameters sharing  Compared to the single-task method, the simple hard parameters sharing model has better results on most benchmark datasets. In particular, it achieves significantly better performance than the single-task method on STS-B dataset, with an improvement of 5.34%.

Linguistic hierarchies  From Table 2, we can observe that exploring linguistic hierarchies has the best overall performance among the compared individual MTL techniques on most datasets. This verifies that the auxiliary basic tasks (i.e., POS tagging, chunking, and dependency parsing) can capture more comprehensive word-level and sentence-level semantic features, thereby yielding the strong performance of three representative NLP tasks. In addition, adding auxiliary basic tasks increases the amount of training data and therefore increases the generalization of the model.
Table 3: Experiment result. The value in the table is the difference between disassembled model and ensemble model (ABCDE or ENS).

|     | SST | CoLA | MNLI | MRPC | QNLI | STS-B | POS | CHUNK | DP |
|-----|-----|------|------|------|------|-------|-----|-------|----|
| AC  | 89.11 | 70.44 | 72.22 | 80.15 | 73.57 | 72.29 | 94.15 | 95.7 | 96.61 |
| BC  | 86.93 | 69.81 | 70.09 | 73.4 | 71.03 | 69.92 | 72.52 | 94.17 | 95.67 | 96.64 |
| AB  | 89.39 | 70.15 | 72.45 | 79.29 | 73.21 | 72.52 | 94.17 | 95.67 | 96.64 |
| ABC | 89.68 | 69.96 | 73.23 | 78.92 | 73.41 | 73.76 | 94.13 | 95.72 | 96.63 |
| ACD | 88.95 | 69.83 | 71.97 | 80.39 | 73.4 | 68.32 | 94.14 | 95.67 | 96.6 |
| ACE | 88.88 | 69.96 | 72.44 | 79.66 | 72.47 | 71.85 | 94.13 | 95.66 | 96.61 |
| ABCD| 88.76 | 70.15 | 73 | 78.68 | 74.91 | 67.92 | 94.16 | 95.61 | 96.64 |
| ABCE| 89.45 | 69.96 | 72.85 | 76.96 | 73.46 | 73.91 | 94.1 | 95.64 | 96.61 |
| ACDE| 88.84 | 69.87 | 71.77 | 80.23 | 72.98 | 66.37 | 94.18 | 95.69 | 96.63 |
| ABCDE| 88.42 | 69.48 | 72.43 | 80.15 | 74.48 | 69.18 | 94.12 | 95.66 | 96.65 |

Table 4: Exploring linguistic hierarchies method with Partial auxiliary tasks result.

|        | SST | CoLA | MNLI | MRPC | QNLI | STS-B |
|--------|-----|------|------|------|------|-------|
| SHPS (w/o basic tasks) | 88.33 | 69.43 | 71.98 | 75.5 | 71.5 | 73.02 |
| POS    | 88.19 | 70.06 | 71.81 | 78.19 | 71.65 | 73.69 |
| Chunking | 88.42 | 69.67 | 72.65 | 77.70 | 72.10 | 73.77 |
| Parsing | 88.88 | 69.58 | 72.97 | 79.62 | 73.31 | 71.29 |
| POS+Chunking | 88.99 | 70.44 | 72.42 | 78.43 | 72.02 | 73.38 |
| POS+Parsing | 88.99 | 69.67 | 72.50 | 81.13 | 73.66 | 71.82 |
| Chunking+Parsing | 89.11 | 71.59 | 72.28 | 81.62 | 72.66 | 71.54 |
| ELH with three basic tasks | **89.45** | 70.06 | 72.1 | 79.78 | 73.44 | 71.49 |

However, we found that combination linguistic hierarchical information would degrade the performance of the model on the STS-B dataset compared with the SHPS and AL models, and we will analyze these results in Section 7.3.

**Gate mechanism** Gate mechanism achieves better results than the single-task model on all data sets. Gate mechanism has an ability to select potentially useful features, which can reduce the interference among tasks [9].

**Label embedding** Surprisingly, label embedding outperforms the single-task model significantly with its lightweight structure. This may be because that label embedding method can leverage label information of each task by mapping labels into dense, low-dimension and real-value vectors with semantic implications, which captures the semantic correlations among tasks.

**Orthogonality constraint** We observe that orthogonality constraint with hard parameters sharing outperforms the single-task model on most datasets, but it is outperformed by the simple hard parameter sharing. This means that orthogonality constraint loss has a negative impact on the MTL model. How can this be explained? Based on error analysis, we find that orthogonality constraint cannot correctly differentiate the shared and private features, but adds interferential information into the learned shared and private features, thus decreasing the performance of the MTL model.

**Adversarial learning** The adversarial learning framework is based on the single hard parameters sharing. Compared with single hard parameters sharing, the performance of adversarial learning framework on different data sets is not stable. For example, on MRPC, the accuracy of adversarial learning framework is 0.92% higher than that of single hard parameters sharing. While on STS-B, adversarial learning results in model performance deterioration. In general, adversarial learning has the smallest impact on model performance over the single-task model, which are not as expected. This may be because that adversarial learning framework updates the opposite gradient of the parameters according to specific tasks.

**Summary** After analyzing the performance of the six MTL methods over the single-task model, we find that linguistic hierarchical information performs better than other individual MTL methods. Gate mechanism is effective but its performance is unstable. Label embedding has a simple structure and performs better than some more complex MTL methods. Orthogonality constraint and adversarial learning framework have limited influence on the model and their results are highly correlated with specific datasets.
Table 5: Similarity scores of the two sentences pairs from STS-B predicted by SHPS and ELH.

| Gold | SHPS  | ELH  | Sentence pairs                                      |
|------|-------|------|-----------------------------------------------------|
| 1.0  | 0.8856| 2.5934| A woman is playing the flute.                        |
|      |       |      | A man is playing a keyboard.                         |
| 1.4  | 1.5472| 2.3639| People ride mopeds in an urban setting.              |
|      |       |      | People riding horses in a fenced area.               |

7.2 Disassemble Analysis

We conduct disassemble analysis of the ensemble model (ENS) to investigate the effectiveness of different combinations of these methods. For the convenience of narration, we use letters A, B, C, D, E to represent hard parameters sharing with linguistic hierarchies, gate mechanism, label embedding, orthogonality constraints and adversarial learning. For example, ABCDE stands for the ensemble model (ENS). The results are summarized in Table 5. From the results, we can observe that the combined methods have different performance on different datasets. For example, removing gate mechanism (i.e., ACDE) will improve the performance of the ENS model on SST-2 by 0.42% but reduce the performance on MNLI by 0.66%. The best performance on most datasets is achieved by the ABC model which combines gate mechanism, label embedding and hard parameters sharing with linguistic hierarchies. The results are consistent with the findings in the previous section, which can be explained that these three MTL methods have no strong correlations, thus combining them will not disturb the performance of each individual MTL method.

7.3 In-depth Analysis of Exploring Linguistic Hierarchies

As shown in Table 2, we can observe that exploring linguistic hierarchies achieves the best performance among the individual MTL methods on most datasets except STS-B. To investigate this unexpected observation, we conduct ablation test to analyze the efficacy of each basic task (i.e., POS tagging, Chunking, dependency parsing) to the performance of ELH method by discarding one or two auxiliary basic tasks each time. Result are shown in Table 4. From Table 4 we can observe that different tasks require different levels of language structure information, and dependency parsing is most profitable for all tasks except STS-B. By doing some error analysis on STS-B dataset, we find that most false positive sentence pairs in STS-B have similar dependency features. Table 5 shows two sentence pairs from STS-B that are incorrectly predicted by ELH. Thus, adding auxiliary dependency parsing task to the MTL framework will make the model pay much attention to dependency features rather than semantic features, resulting in incorrect predictions.

7.4 Overfitting Analysis

Multi-task learning is supposed to alleviate the overfitting problem by leveraging useful information contained in multiple related tasks to improve the generalization performance of all the tasks. Based on our empirical observation, there is high-risk of overfitting on STS-B dataset. To investigate the performance of the six MTL methods on alleviating overfitting problem, we illustrate the learning curves of these models in Figure 2, where each method iterates over more than 400 epochs. From the results, we can observe that all six MTL methods can alleviate the overfitting problem. In particular, both hard parameter sharing and adversarial learning methods greatly reduce the risk of overfitting. While exploring linguistic hierarchies and orthogonality constraint cannot make the MTL model less prone to overfitting.

8 Conclusion

In this work, we explored the efficacy of six widely used MTL tasks proposed in recent studies on multi-task learning with deep neural networks. We found that 1) all six individual MTL methods contribute great improvements to the overall performance on the six benchmark datasets; 2) using linguistic hierarchical information performs better than other individual MTL methods; 3) combining gate mechanism, label embedding and hard parameters sharing with linguistic hierarchies can achieve best results on a broad range of NLP tasks.

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Figure 2: Overfitting on STS-B(smoothed)

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