Adaptive Noise Injection: A Structure-Expanding Regularization for RNN

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Abstract
The vanilla LSTM has become one of the most potential architectures in word-level language modeling, like other recurrent neural networks, overfitting is always a key barrier for its effectiveness. The existing noise-injected regularizations introduce the random noises of fixation intensity, which inhibits the learning of the RNN throughout the training process. In this paper, we propose a new structure-expanding regularization method called Adjective Noise Injection (ANI), which considers the output of an extra RNN branch as a kind of adaptive noises and injects it into the main-branch RNN output. Due to the adaptive noises can be improved as the training processes, its negative effects can be weakened and even transformed into a positive effect to further improve the expressiveness of the main-branch RNN. As a result, ANI can regularize the RNN in the early stage of training and further promoting its training performance in the later stage. We conduct experiments on three widely-used corpora: PTB, WT2, and WT103, whose results verify both the regularization and promoting the training performance functions of ANI. Furthermore, we design a series simulation experiments to explore the reasons that may lead to the regularization effect of ANI, and we find that in training process, the robustness against the parameter update errors can be strengthened when the LSTM equipped with ANI.

1. Introduction
As a foundational component of natural language processing (NLP), language modeling plays an important role of systems in machine translation (Koehn, 2009), speech recognition (Yu & Deng, 2014) and natural language generation (Radford et al., 2017; Merity et al., 2017). The RNN-based model is one of the mainstreams of word-level language modeling (Zilly et al., 2016; Kim et al., 2016; Shen et al., 2017; Mikolov et al., 2010; Melis et al., 2017), but their performance has long been hindered by overfitting.

In addition to language modeling, overfitting is also a tricky problem for RNNs in a variety of other NLP tasks, which contributes to the emergence of regularization techniques. For narrowing the gap between the training and validation performance, the existing RNN regularizations work by artificially introducing some extra parameter-free mechanisms during training, where the noise injection mechanisms are the most successful one and spawn diverse regularization techniques in RNN-based language models (Zaremba et al., 2014; Gal & Ghahramani, 2016; Dieng et al., 2018; Krueger et al., 2016; Wan et al., 2013). Besides, the regularization of weight decay (Krogh & Hertz, 1992) adds a parameter constraint mechanism, the recurrent batch normalization (Cooijmans et al., 2016) and layer normalization (Ba et al., 2016) apply a normalization mechanism to the summed inputs within each layer. There is also a kind of method called structure regularization (Sun, 2014), which proposes a special training sample processing mechanism for structured prediction.

Different from these existing regularizations explicitly introduce the special parameter-free mechanisms, we aim to regularize a given RNN by directly expanding its structure with an external learnable network. This kind of regularization is equivalent to upgrading the architecture of the original RNN to obtain a certain regularization ability. Moreover, it can work in conjunction with the parameter-free mechanisms introduced by the other existing regularizations to further improve the model performance.

However, there are two key challenges for the implementation of the structure-expanding regularization: hypothesis space inconsistency and complexity conflict. The hypothesis space inconsistency is a main theory obstacle for the structure-expanding regularization. The concept of overfitting is based on a specific hypothesis space, once the external structure is incorporated, the hypothesis space of the original RNN model will change accordingly. Therefore, one risk is that the overfitting degrees before and after the RNN is expanded may be incomparable, which will lead
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to the regularization function of the structure expansion is unprovable. As for the complexity conflict, the model complexity is likely to be enhanced after the RNN is expanded, which may even further increase the risk of overfitting, violating the motivation of regularizing.

In this paper, we separately overcome the above two challenges, and successfully implement an easy-to-adjust structure-expanding regularization for the RNN in RNN-based language model called Adaptive Noise Injection (ANI). As far as we know, in the field of NLP, ANI is the first technique to regularize a model by directly expanding the original model structure rather than adding the special parameter-free mechanisms. Different from the existing regularizations using noise with fixation strength, the idea of ANI is to introduce an extra RNN and generate an adaptive noise for the last RNN layer output of the original language model.

We conduct experiments on three standard benchmark corpora: Penn Treebank, WikiText-2, and WikiText-103. The experiments demonstrate that ANI can regularize the RNN in the language model when it overfits; on the other hand, ANI can improve the training performance in the case where the overfitting is not serious, thereby strengthening the model generalization from another aspect. As a structural upgrade for the RNN, ANI can be directly integrated into the existing regularized RNN language model to work effectively without increasing the burden of adjusting the model hyper-parameters. Furthermore, we also design a series of simulation experiments to explore the double-branch structure of LSTM using ANI, whose results show that the double-branch LSTM structure is inherently more robust against the parameter update errors that occur in training process than the existing single-branch structure which is beneficial for alleviating the overfitting.

2. Our Approach

2.1. Motivation

Although the existing noise-injected regularizations add noises to RNN of different form (e.g., binomial distribution, normal distribution), the intensity of their noises is fixed, which will inevitably sacrifice certain expressiveness of the RNN and lead to the degradation of training performance. In the case where the overfitting is apparent (e.g., the validation performance rebounds and gradually deteriorates after training to a certain extent), we can directly give up the superfluous expressiveness and strength the noise intensity for an effective regularization. But when the noise intensity increases to a certain extent, it is bound to occur that the validation performance keeps improving as the training performance. At this point, it is difficult for us to choose between the stronger regularization and better expressiveness, which leads to a tedious fine-tuning for each hyper-parameters. On the other hand, the incompatibility of some regularizations with different noise injection mechanisms is also a problem. For example, the RNN dropout in (Zaremba et al., 2014), Variational dropout (Gal & Ghahramani, 2016), Zoneout (Krueger et al., 2016) and Noisin (Dieng et al., 2018) all introduce the noises of different forms into the RNN outputs and should be selected by pre-experiments in actual use, which will consume extra computational resources and time.

In consideration of the above analysis, we envisage introducing an adaptive noises into the RNN. In the early stage of training, the adaptive noise can interfere with model learning and play the role of regularizing to some extent, as the training progresses, the noise can be weakened to restore a part of expressiveness of the RNN and even help it to further improve the training performance. In this way, when the RNN overfits seriously, the adaptive noise can regularize it in the early training stage; when the overfitting is unobvious, it can further enhance the model generalization by improving the training performance, which can be seen as a softer way to alleviate the conflict of choosing to increase the noise intensity or maintain the RNN expressiveness in fine-tuning the hyper-parameters.

Since the impact of the adaptive noise on the RNN is from suppression to improvement, which coincides with the trend of the training itself (i.e., from bad to good). Therefore, we naturally think to use the output of an additional RNN branch as the adaptive noise for the output of the last RNN layer (also is the context vector) in RNN language model, thereby influencing all parameter update of each RNN layer by layer in back propagation. Given this idea, we propose Adaptive Noise Injection (ANI) as a structure-expanding regularization. As a structural improvement of RNN, ANI is compatible with the other existing noise-injected regularizations that introduce the parameter-free noise mechanisms.

2.2. Adaptive Noise Injection

In a multi-layer RNN language model, assume that \(E = (e_1, ..., e_n), e_j \in \mathbb{R}^{d_e}\) are the embedding of the \(n\)-word input sequence. We regard the multi-layer RNN as the main branch, and the outputs of the last RNN layer are denoted as \(H = (h_1, ..., h_n), h_j \in \mathbb{R}^{d_h}\). We regard the multi-layer RNN as the main branch, and the outputs of the last RNN layer are denoted as \(H_A = (h_{A1}, ..., h_{An}), h_{Aj} \in \mathbb{R}^{d_{A}}\) \((d_A \leq d)\). We introduce the adaptive noise \(H_A\) into \(H\) by means of local feature summation:

\[
y_j = h_j + P \cdot h_{Aj}, j = 1, \ldots, n
\]
\[
P = (I_{d_A}; 0)^T
\]
where \( Y = (y_1, \ldots, y_n) \) is the results of the ANI, \( I_{d_A} \in \mathbb{R}^{d_A \times d_A} \) is the identity matrix, \( 0 \in \mathbb{R}^{d_A \times (d_A - d_A)} \) is a zero matrix, and the projection matrix \( P \) is used to map \( h_{A_j} \) into a \( d_A \)-dimension vector with zero padding. In Equation (1), the form of \( y_j = (h_j^{(1)} + h_j^{(2)} + \cdots + h_j^{(d_A)} + h_{A_j}^{(d_A)}, h_j^{(d_A+1)}, \ldots, h_j^{d_d}) \). The expanded RNN with ANI is denoted as RNN-ANI, whose outputs are fed into the Softmax Layer for predicting. We refer to the first \( d_A \) features of \( y_j \) as as noised features and the value of \( d_A/d \) as noised proportion.

Different from other existing noise-injected regularizations, ANI adds the adaptive noise to the specific features within the main-branch RNN outputs by local feature summation. The recursion of the main-branch RNN is the core for the effectiveness of ANI, which makes every feature within its outputs (starting from the second time step) controlled by all of its parameters in forwarding propagation. So in back propagation, even though we only add adaptive noises to a part of output features, the gradients of the noised features can flow to all parameters of the last main-branch RNN and influence their updates, and then arrive at the previous RNN layers. On the other hand, since the neural network is trainable, and the only difference between two different noised feature selection schemes is equivalent to a linear transformation of the mean branch output, similar to the inference of (Inan et al., 2016), we believe that different selection schemes are equivalent to Equation (1-2) when noised proportion is determined\(^1\).

Next, we solve the two challenges for the structure-expanding regularization ANI: hypothesis space inconsistency and complexity conflict.

[Hypothesis Space Inconsistency] After employing ANI, the hypothesis space for the given RNN (denoted as \( H \)) is changed to a new space for RNN-ANI (denoted as \( H' \)), which will lead to the overfitting degrees of RNN and RNN-ANI are incomparable.

To solve the problem, we unify the two hypothesis spaces by mapping \( H \) to a subset of \( H' \). We can force the existing common RNNs (e.g., the standard RNN, LSTM (Hochreiter & Schmidhuber, 1997), GRU (Cho et al., 2014)) to output zero vector for any input by fixing their parameters to zero. Therefore, the RNN before using ANI can be rewritten as a special case of LSTM-ANI, and all parameters of the extra RNN branch is fixed to zero. In this way, the original hypothesis space \( H \) is mapped into a subspace of the new space \( H' \), which can be regarded as the common hypothesis space of the LSTM and LSTM-ANI.

In the same hypothesis space \( H' \), assume that the training and validation performances of a model \( M \) are denoted as \( T(M) \) and \( V(M) \), under the definition of overfitting (Mitchell, 1997), if:

\[
T(\text{RNN} - \text{ANI}) - T(\text{RNN}) < 0 \quad \text{and} \quad V(\text{RNN} - \text{ANI}) - V(\text{RNN}) > 0
\]

we can judge the overfitting degree of RNN-ANI is lower than the original RNN\(^2\).

[Complexity Conflict] Complexity conflict is the main obstacle to implementing ANI. Since we incorporate an extra RNN branch with the main-branch RNN, if the complexity of the extra branch is too high, the ANI will fail to regularize the model and even increase the risk of overfitting. In order to prevent the excessive increase of model complexity, we only use RNN of a single layer as the extra branch in this paper. Furthermore, for controlling the complexity of the extra branch, we can adjust the noised proportion to decide its hidden size, thereby deciding its parameter count\(^3\).

For a specific type of the extra RNN branch, although smaller noised proportion can prevent excessive increase in complexity, too low a noised proportion will result in the failure of ANI. In fact, the original RNN can be seen as a special RNN-ANI with zero as noised proportion, if the noised proportion is too small, the influence of the adaptive noise to each parameter of main-branch RNN will be too weak, which will lead to the function of both the regularization in the early training stage and the promotion of the training performance in the latter training stage be invalid. So the hyper-parameter of noised proportion should be adjusted to an appropriate value. The noised proportion is crucial for using ANI, and we will discuss its significance in the second explanation for ANI of Section 2.3.

2.3. A Second Explanation for ANI

In the previous description, we interpret ANI as adding adaptive noises to the specific features within the output of the last RNN layer in the language model. In this subsection, we provide another explanation for ANI from its double-branch structure by an intuitive analogy.

For a language model which employs multi-layer RNN to extract the semantic features from the input embeddings, \(^2\)About more detail of hypothesis space inconsistency, please see Appendix II for details.

\(^3\)In addition to adjusting noised proportion, we can also employ different types of RNN in extra branch to control the complexity of the extra branch. However, adjusting both RNN type and noise proportion will increase the cost of using ANI. For LSTM or GRU as the extra branch, we find that only adjust the noise proportion can achieve ideal results. Therefore, we do not consider adjusting RNN type of extra branch in the theoretical part. In the experimental part of Section 3.1, we will give relevant experiments.
we can imagine the entire multi-layer RNN as a student . When the learning ability of \( \mathcal{A} \) ( i.e. , expressiveness of the RNN) is too strong, he is likely to learn some complicated and wrong knowledge ( i.e. , some complex patterns which exist in the training set but not in the real data distribution) during training. To prevent him from learning these wrong knowledge, the existing regularizations explicitly add various constraints ( i.e. , parameter-free mechanisms) to restrict his learning ability. Different from these regularizations, ANI introduces another student \( \mathcal{B} \) whose learning ability is significantly weaker than \( \mathcal{A} \), and enforce \( \mathcal{A} \) and \( \mathcal{B} \) to learn jointly ( i.e. , the double branch of ANI). Under this cooperative mode, \( \mathcal{B} \) will slow down the overall learning speed due to the weak learning ability, and cause the hysteresis of the improvement of overall training performance in the early training stage. However, \( \mathcal{B} \) only need to share part of work of \( \mathcal{A} \) ( i.e. , noised proportion \( \leq 1 \)), which leads to the fact that as the training progresses, it is entirely possible for \( \mathcal{B} \) to get better and complete the common tasks ( i.e. improve noised features), thus getting rid of the hysteresis and even making the final training performance surpass \( \mathcal{A} \) working alone.

In the second explanation for the regularization and promotion of training performance of ANI, the noised proportion controls both the learning ability ( i.e. , complexity) and tasks difficulty ( i.e. , the number of noised features) of \( \mathcal{B} \). When we weaken the learning ability of \( \mathcal{B} \), the task difficulty is also eased, so it is possible for \( \mathcal{B} \) to cooperate \( \mathcal{A} \) to learn the training set better.

Due to the extra RNN branch straightly skips from the embedding layer to the last Softmax layer, it can be seen as a variant of skip connection ( Srivastava et al., 2015; Huang et al., 2016; Zilly et al., 2016), which can effectively alleviate the vanishing gradient problem in training as the number of RNN layers increases. A clear difference between RNN-ANI and the double-branch frameworks of skip connection ( Srivastava et al., 2015; Huang et al., 2016) and model fusion ( Feichtenhofer et al., 2016) is that there is a significant gap between the status of the main branch and the extra branch in RNN-ANI. The teacher-student model and the supervision-guided autoencoder ( SUGAR) ( Zhang et al., 2014) are another framework that has some similarities with RNN-ANI. However, these two networks will discard one branch and only retain the other after training is completed. In contrast, ANI only extends the structure of the RNN without other additional operations.

2.4. The Usage of ANI

For both the explanations, ANI actually takes advantage of the trend of training itself from bad to good. But different from the existing noise-injected regularizations freely control the regularization strength by changing the noise intensity ( i.e. , dropout rate), the regularization ability of ANI is limited, because either the noised proportion is too large or too small, its regularization ability will be invalidated. We find that ANI is more suitable for the case where the overfitting is not serious, otherwise, using ANI alone may not be enough. To this end, we tend to use ANI together with the existing RNN regularizations. ANI can be seen as a supplement for these existing regularizations, which can not only further regularize the RNN in the early training stage but also promote the training and validation performance in the later training stage.

Because the magnitudes of the RNN hidden size of in the existing language model are on the order of hundreds to thousands, our various experimental results show that directly setting the noised proportion to 1/10 can stably improve the language model performance while hardly increasing the model complexity.

Another question is whether we need to introduce adaptive noises to other RNN layers in multi-layer RNN language model. In our previous experiments, we attempted different strategies of adding adaptive noise to different RNN layers in language models, and the results showed that the other RNN layers adaptive noises did not further improve the final results effectively, we infer that the effect of the last RNN layer adaptive noise masks the others. As a result, to make our approach effective and as easy to adjust as possible in practical applications, we only add one extra branch for the top RNN layer output as in Section 2.2.

3. Experiments

The experiments are divided into two parts: ordinary experiments and simulation experiments, which are mainly based on multi-layer RNN language model. The evaluation metric is perplexity ( PPL) computed as

$$P(w_1, \ldots, w_{i-1}) = \frac{1}{N} \sum_{i=1}^{N} \log \left( \prod_{j=1}^{i} P(w_i | w_1, \ldots, w_{i-1}) \right),$$

where

$$P(w_i | \text{context})$$

is the conditional probability of the \( i_{th} \) word calculated by the language model. The corpora include preprocessed version of Penn Treebank ( PTB) ( Mikolov et al., 2010), the WikiText-2 ( WT2) ( Merity et al., 2016) and WikiText-103 ( WT103) ( Merity et al., 2016), whose statistical results are presented in Appendix II.

3.1. Ordinary Experiments

The ordinary experiments include three subsections, which respectively explore one characteristic of ANI. **Subsection 1:** ANI can work in conjunction with the other RNN regularizations when the language model overfits. **Subsection 2:** Even if overfitting is unobvious, ANI can enhance the model generalization by further improving its training performance. **Subsection 3:** ANI has both functions of regularization and promoting the training performance, and we
can make a trade-off between these two functions by adjusting the noised proportion.

[Subsection 1 (S1)] For proving ANI can work in conjunction with the other RNN regularizations, we apply the AWD-LSTM (Merity et al., 2017) as the baseline, and the corpora are PTB and WT2. In experiments, we separately attempt standard RNN, LSTM, and GRU as the extra branch of ANI, and observe the effects of different noised proportions. As in Section 2.2, we feed the same input of the main branch (the input word embeddings) into the extra branch, so we only fine-tune the dropout rate of the input word embeddings to accommodate the new double-branch structure and keep the other hyper-parameters unchanged. We train each language model for two stages: with and without fine-tune, and the fine-tuned model results are presented in Table 1.

For standard RNN as the extra branch, we only set the noised proportion to 1/20, because the interference of the extra RNN output to the main branch is too serious, and the higher noised proportion will excessively hinder the learning of the model. Compared with LSTM and GRU, the expressiveness of the standard RNN is too weak, and increasing the noised proportion will not effectively enhance it, but cause the RNN outputs destroy more features of the main branch output. For both LSTM and GRU, we can clearly observe that ANI with the noised proportion as 1/10 significantly improves the effect of the original AWD-LSTM on the two corpora, the validation and test PPL respectively drop 2.1 and 1.8 points on PTB and 2.2 and 2.3 on WT2 after we fine-tune the dropout of input word embedding.

With the increase of the noised proportion, although the expressiveness of the extra branch can be enhanced, its burden is also aggravated (i.e., the noised features involved by it increase), so we cannot predict whether the expressiveness of the extra branch is sufficient to complete its corresponding task under a specific noised proportion. As in Table 1, we cannot easily observe the correlation between the noised proportion and the final effect. But one distinct phenomenon is that 1/10 always outperform the other noised proportions with the negligible cost of additional parameters. Taken together, although on the surface ANI introduces the type of the extra branch and the noised proportion as the new hyper-parameters, in fact, we can directly use a standard setting that applies LSTM or GRU as the extra branch and setting the noised proportion to 1/10.

[Subsection 2 (S2)] We have verified that ANI can cooperate with the existing regularizations to improve the model performance when it overfits. But in most cases, overfitting does not occur seriously (e.g., when the regularization hyper-parameters of the language model have been adjusted well enough (the case in S1) or training a large corpus). At this point, it is difficult for these existing regularizations to improve the model generalization, because the model is often sensitive to their hyper-parameters, which is hard to be fine-tuned. In this subsection, we show that ANI can still significantly improve the model performance under the standard setting for these cases. We construct several middle-sized LSTM language model in (Zaremba et al., 2014) with different LSTM layers and remove their corresponding regularizations. Under the same frameworks, we set whether to use ANI (i.e., extra branch type: LSTM, noised proportion: 1/10) as the only experimental variable. In addition, we adopt a more realistic corpus: WikiText-103 (WT103). The experiments are divided into four groups: I, II, III, IV, corresponding to the four different language models with 1, 2, 3, and 4 LSTM layers, whose results are in Table 2. Also, we find the overfitting for all the four group model is unobvious, ANI improves the model generalization by further pulling down the training PPL. Taking the Group III as an example, we draw the training and validation PPL trend curves of LSTM-III and LSTM-ANI-III in Figure 1.

From Table 1, the cost of parameters for building the extra LSTM branch of ANI is less than 1% of the total parameter count for each LSTM language model. But with the help of ANI, the final training PPL of each LSTM language model drop by 2.6/2.9/6.1/8.7, the validation PPL drop by 2.3/2.7/4.9/6.4, and the test PPL drop by 1.6/2.3/5.2/6.9. We can observe that as the number of LSTM layers in the main branch increases, the improvement bring by ANI becomes more and more significant. In Figure 1 (a) and (b), we can clearly see that the validation PPL of LSTM-III does not rebound during the entire training process, but continues dropping with the training PPL, and eventually tends to be stationary. The situation in Figure 1 is usually sensitive to the existing regularization hyper-parameters because too strong regularization will weaken the model expressiveness. But for LSTM-ANI-III, we can find that the falling speed of its training PPL is slower than LSTM-III in the first 13 epochs, which is a normal phenomenon in LSTM-ANI because the two branches need to have a process for mutual adaption, and it is consistent with the second explanation in Section 2.3. Comparing the training and validation PPL of the two language models, we can conclude that the enhancement of LSTM-ANI validation performance comes from the improvement of its training effect.
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Table 1. The PPL of AWD-LSTM and different variants of AWD-LSTM-ANI on PTB and WT2, we respectively use RNN, GRU and LSTM as the extra branch of ANI, and for LSTM as the extra branch, we attempt the noised proportions of $1/20$, $1/10$, $3/10$, $5/10$, $7/10$ and $10/10$. EmbDrop refers to the input embedding dropout rate. #Param denotes parameter count.

| EmbDrop is same as in (Merity et al., 2017). | PTB (EmbDrop=0.4) | WT2 (EmbDrop=0.65) |
|---------------------------------------------|--------------------|--------------------|
|                                             | #Param  | Valid | Test  | #Param  | Valid | Test  |
| AWD-LSTM $^1$                              | 24.2   | 60    | 57.3  | 33.6   | 68.6  | 65.8  |
| AWD-LSTM-ANI-RNN-1/20                      | 24.2   | -     | -     | 33.6   | 69.9  | 66.9  |
| AWD-LSTM-ANI-GRU-1/10                      | 24.3   | 59.1  | 56.3  | 33.6   | 66.9  | 63.8  |
| AWD-LSTM-ANI-LSTM-1/10                     | 24.3   | 59.0  | 56.4  | 33.6   | 66.7  | 64.4  |

| EmbDrop is fine-tuned by us. | PTB (EmbDrop=0.52) | WT2 (EmbDrop=0.675) |
|-------------------------------|--------------------|--------------------|
|                               | #Param  | Valid | Test  | #Param  | Valid | Test  |
| AWD-LSTM-ANI-RNN-1/20         | 24.2   | 62.3  | 59.5  | 33.6   | 69.6  | 67.6  |
| AWD-LSTM-ANI-GRU-1/10         | 24.2   | 58.0  | 56.0  | 33.6   | 66.7  | 63.9  |
| AWD-LSTM-ANI-LSTM-1/20        | 24.2   | 57.9  | 55.8  | 33.6   | 66.9  | 64.2  |
| AWD-LSTM-ANI-GRU-1/10         | 24.3   | 58.0  | 55.7  | 33.6   | 66.5  | 63.5  |
| AWD-LSTM-ANI-LSTM-1/10        | 24.3   | 57.9  | 55.5  | 33.6   | 66.4  | 63.9  |
| AWD-LSTM-ANI-LSTM-3/10        | 24.5   | 58.3  | 56.2  | 33.8   | 66.7  | 64.5  |
| AWD-LSTM-ANI-LSTM-5/10        | 24.7   | 58.7  | 56.5  | 34.0   | 66.8  | 64.3  |
| AWD-LSTM-ANI-LSTM-7/10        | 25.0   | 59.0  | 56.5  | 34.3   | 66.2  | 63.8  |
| AWD-LSTM-ANI-LSTM-10/10       | 25.5   | 59.3  | 57.0  | 34.8   | 67.1  | 64.8  |

Table 2. The training, validation and test PPL of LSTM language models before and after using ANI in each group on WT103 corpus, where the training PPL is the average of all mini-batches in the corresponding epoch.

| group | I | II | III | IIII |
|-------|---|----|-----|-----|
| Use ANI | No | Yes | No | Yes |
| #Param(M) | 351.7 | 351.9 | 355.1 | 355.3 |
| Train | 60.9 | 58.3 | 49.2 | 56.3 |
| Valid | 67.0 | 64.7 | 57.4 | 54.7 |
| Test | 68.4 | 66.8 | 59.0 | 56.7 |

Figure 1. The training PPL (a) and validation PPL (b) trend curves of LSTM-III and LSTM-ANI-III (Group III) on WT103.

[Subsection 3 (S3)] In S1 and S2, we have demonstrated that ANI is easy-to-adjust and effective under the existing widely-used frameworks of LSTM language models (Merity et al., 2017; Zaremba et al., 2014). In this subsection, we will intuitively show the functions of regularization and promoting the training performance of ANI, and prove that the strength of these two function can be exchanged to some extent by adjusting the noised proportion. We firstly build a two-layer LSTM language model as in S2 group II and obtain another GRU language model by replacing its LSTM with the GRU of the same size. We separately add the extra branch of ANI with the same RNN type of the
corresponding main branch to both language models and observe the trends of training and validation PPL on PTB corpus under different noised proportions (i.e., 1/10, 2/10, 5/10, 10/10). Figure 2 plots the training and validation PPL of these two kinds of RNN language models.

In Section 2.2, we have solved the problem of hypothesis space inconsistency, so the overfitting degrees of different RNN language models before and after using ANI are comparable. In Figure 2 (a) and (c), the trends of different model training PPL are similar. But through the partial enlargement of the GRU models in (a), we can rank the GRU models by their training performance:

\[ T(\text{ANI} - 10/10) > T(\text{ANI} - 5/10) > T(\text{GRU} - \text{only}) > T(\text{ANI} - 2/10) > T(\text{ANI} - 1/10) \]

and the rank of LSTM models training performance in (c) is:

\[ T(\text{ANI} - 10/10) > T(\text{LSTM} - \text{only}) > T(\text{ANI} - 5/10) > T(\text{ANI} - 1/10) > T(\text{ANI} - 2/10) \]

If we exclude GRU-only (LSTM-only), the training performance of the language model improves with the increase of noised proportion, which indicates that the extra branch with stronger expressiveness (i.e., when we increase the noised proportion, the hidden size and complexity of the extra branch is correspondingly increased, so its expressiveness becomes stronger) can better cooperate with the main branch and obtain a better training performance in the later stage of training. On the other hand, the rank of the final validation PPL of GRU language models is:

\[ V(\text{ANI} - 1/10) > V(\text{ANI} - 2/10) > V(\text{ANI} - 5/10) > V(\text{GRU} - \text{only}) > V(\text{ANI} - 10/10) \]

and the rank of LSTM language model validation PPL is:

\[ V(\text{ANI} - 2/10) > V(\text{ANI} - 5/10) > V(\text{ANI} - 1/10) > V(\text{LSTM} - \text{only}) > V(\text{LSTM} - 10/10) \]

According to Equation (3), we can conclude that the overfitting of ANI-1/10 and ANI-2/10 is weaker than GRU-only in GRU language models, and the overfitting degrees of ANI-1/10, ANI-2/10, and ANI-5/10 are lower than LSTM-only in LSTM language models. This demonstrates that with the proper noised proportion, the hysteresis of the extra branch to the main branch will have a certain regularization effect in the early stage of training. So the validation PPL rebound of ANI-1/10, ANI-2/10, and ANI-5/10 is effectively weakened than GRU-only and LSTM-only in the later training process ((b) and (d)), which is more obvious in (d). However, the regularization effect of ANI will be weakened as the noised proportion increases, when the noised proportion is set to 10/10, the overfitting is even more serious than the original language models in (b) and (d).

In summary, in this subsection, we demonstrate that the ANI has both the functions of regularization and promoting the training performance, and as the noised proportion increases, the regularization effect will be weakened, but the function of promoting the training performance can be strengthened. We can adjust according to the actual situation to get the ideal model generalization. On the other hand, we can find that the regularization effect of ANI is limited, when overfitting is serious, ANI can be used as a supplement regularization of the existing other regularizations as in S1.

3.2. Simulation Experiments

In essence, ANI is a structural improvement for RNN with regularization function, and the form of RNN-ANI with noised proportion = 1 is similar to the other existing double-branch network (He et al., 2016). But in Section 3.1 S3, we can find that both the LSTM-ANI and GRU-ANI model with noised proportion set to 1 (i.e. ANI-10/10) often do not have regularization effects and even aggravate the overfitting. In this section, we design a simulation experiment to further explore the regularization functions of the special double-branch structure of RNN-ANI with different noised proportions.

Although the factors of overfitting are various, overfitting occurs in back propagation of training process, so we believe that these factors mislead the model by causing the update errors to some parameters, thereby making the model more biased towards the rules of training set rather than the rules of real data distribution. As a result, the parameter update error is a direct reason for overfitting, and we guess that the regularization effect of RNN-ANI is correlated to its robustness against the parameter update errors.

In Section 3.1 S3, without the interference of any other techniques, we have demonstrated that LSTM-ANI with different noised proportions has different levels of regularization effect. In this experiment, we still train LSTM-only and ANI-1/10, ANI-2/10, ANI-5/10, ANI-10/10 on PTB corpus. Consistent with the usual practice, we train each language model and use the point corresponding to the best validation performance as the experiment object. We use the noises generated by a Gaussian distribution to simulate
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Figure 2. The training PPL (a) and validation PPL (b) trend curves of LSTM-III and LSTM-ANI-III (Group III) on WT103.

Figure 3. The variation of PPL on PTB 238 test set with the noised parameter ratios from 0 to 100%, the $\sigma = 0.05$ and 0.1 in (a) and (c), (b) is the difference between the models of LSTM-ANI and LSTM-only at $\sigma = 0.05$.

the parameter update errors and leverage a Bernoulli distribution to control the scope of noised parameters. Different from the adversarial perturbations (Zheng et al., 2016; Elsayed et al., 2018) that test the model robustness by adding noised data, our simulation experiments are concerned with the parameter update errors that lead to overfitting during training, so we add noises to the parameters of each LSTM. Concretely, assume that $W_s$ denotes the set of the parameters specified by us for adding noises, we add parameter noises to $W_s$ as:

$$W_s \leftarrow W_s + B_s \cdot N_s$$

where $B_s \sim \text{Bernoulli}(P)$ and $N_s \sim \mathcal{N}(0, \sigma^2)$ are in-
dependent random variables whose shapes are same as $W$, and the elements of them are independent to each other. We found that the trained LSTM parameters are most less than 0.1, so we set $\sigma = 0.05$ and 0.1, then adjust the value of $P$ to control the ratio of noised parameters. To ensure credibility, each result of different simulation experiments is the average of 5 runs. Figure 3 records the variation of PPL on PTB test set with the noised parameter ratios $P$ from 0 to 100%, the $\sigma = 0.05$ and 0.1 in (a) and (c), (b) is the difference between the models of LSTM-ANI and LSTM-only at $\sigma = 0.05$.

In Figure 3 (a) and (c), the test performance of all models become worse as the proportion of noised parameters increases (i.e., test PPL increase). But we can observe that the test PPL curve of LSTM-only is always higher than the curves of ANI-1/10, ANI-2/10, ANI-5/10 in (a) and (c), and the gaps between them are also widened ((b) and (c)), which indicates that this three double-branch models are more robust than LSTM-only against the parameter noises. When $\sigma = 0.05$, the robustness of ANI-10/10 and LSTM-only is hard to distinct, but for $\sigma = 0.1$, all the LSTM-ANI models are better than LSTM-only. In summary, the robustness of the traditional double-branch network (noised proportion = 1) is unobvious when the parameter update errors are not serious, but for the LSTM-ANI with proper noised proportions, the damage of parameter update errors can be significantly reduced, which is beneficial for alleviating the overfitting.

4. Conclusion

In this paper, we propose a structure-expanding regularization for RNN named Adaptive Noise Injection (ANI), and separately use a subspace projection method and a local feature summation to solve the two obstacles of hypothesis space inconsistency and complexity conflict. Moreover, we explain the principle of ANI from two perspectives and give a universal usage of ANI for RNN language model. The experiments are divided into two parts: ordinary experiments and simulation experiments involving three widely-used corpora: PTB, WT2, and WT103. Through the ordinary experiments, we demonstrate that ANI can not only further improve the existing regularized RNN language models, but also effectively enhance the model generalization by promoting its training performance when overfitting is unobvious. In addition, the effects of regularization and promoting training performance can be exchanged by adjusting the noised proportion of ANI. In the simulation experiments, we prove the double-branch structure of ANI is more robust than the general single-branch RNN structure against the parameter update errors, and this robustness can be strengthened by properly adjusting the noised proportion.

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A. Appendix I: Supplement for Section 2

A.1. The influence sphere of adaptive noise (Section 2.2)

In Section 2.2, we pointed out that even the noised features only account for a part of features within main branch output, the recursion of the RNN enables all its parameters to be influenced by the gradients of the noised features. Now we give the corresponding mathematical derivation, for an L-layer RNN language model⁶, we only need to consider the gradient flow in its top two RNN layers (if L = 1, we only need to consider the only LSTM).

Assume that \( x_j \in \mathbb{R}^{d_x} \) is the \( j \)-th input embedding vector of the main-branch RNN, and the \( l \)-th layer RNN output corresponding it is \( v_{l,j} \in \mathbb{R}^{d_l} \), the operation of the top RNN is:

\[
v_{L,j} = f(W_L \cdot v_{L-1,j} + U_L \cdot v_{L,j-1} + b_L) \quad (1*)
\]

where \( W_L \in \mathbb{R}^{d_L \times d_{L-1}} \) is the non-recurrent parameter matrices; \( U_L \in \mathbb{R}^{d_L \times d_L} \) is the recurrent parameter matrices. \( b_L \in \mathbb{R}^{d_L} \) is the bias, \( f \) is the element-wise nonlinear activation function (e.g. sigmoid, tanh). In RNN-ANI, \( v_{L,j} = (v_{L,j}^N, v_{L,j}^O) \) is the concatenation of the \( d_A \)-dimension noised features (denoted as \( v_{L,j}^N \)) and other features (denoted as \( v_{L,j}^O \)). Correspondingly, the generation of \( v_{L,j}^N \) and \( v_{L,j}^O \) are as:

\[
v_{L,j}^N = f(N_w \cdot v_{L-1,j}^N + N_u \cdot v_{L,j-1}^N + b^N) \quad (2*)
\]

\[
v_{L,j}^O = f(W_L^O \cdot v_{L-1,j} + U_L^O \cdot v_{L,j-1} + b^O) \quad (3*)
\]

From Equation (2*), we can see that the gradients of \( v_{L,j}^N \) can flow into each features of the output of the last RNN layer \( v_{L-1,j} \), so the update of all parameters in the previous RNN layers will be influenced by the noised features. For an arbitrary parameter \( W_{L}^{(p,k)} \) \((p \in \{1, \ldots, d_A\}, k \in \{1, \ldots, d_L-1\})\) within \( W_L \) in L-th RNN, its gradient is calculated as:

\[
\frac{\partial \text{Loss}}{\partial W_{L}^{(p,k)}} = \sum_{j=1}^{n} \frac{\partial \text{Loss}}{\partial v_{L,j}} \frac{\partial v_{L,j}}{\partial W_{L}^{(p,k)}} = \sum_{j=1}^{n} \frac{\partial \text{Loss}}{\partial v_{L,j}^N} \frac{\partial v_{L,j}^N}{\partial W_{L}^{(p,k)}} + \sum_{j=1}^{n} \frac{\partial \text{Loss}}{\partial v_{L,j}^O} \frac{\partial v_{L,j}^O}{\partial W_{L}^{(p,k)}} \quad (4*)
\]

Here, for \( \beta \in \mathbb{R}^{d_a}, \gamma \in \mathbb{R}^{d_b} \), we define \( \frac{\partial \beta}{\partial \gamma} = \left[ \frac{\partial \beta_{a}}{\partial \gamma_{b}} \right] \), \( a = 1, \ldots, d_a, b = 1, \ldots, d_b \). We only focus on the gradients through the interacted features of each hidden states \( v_{L,j}^N, j \in \{1, \ldots, n\} \):

\[
\frac{\partial v_{L,j}^N}{\partial W_{L}^{(p,k)}} = \left\{ \begin{array}{ll}
 f_p' \cdot v_{L-1,j}^N + \frac{\partial v_{L,j}^N}{\partial (v_{L,j-1}^N)} \cdot \frac{\partial v_{L,j-1}^N}{\partial W_{L}^{(p,k)}}, & \text{if } p \leq d_A \\
 \frac{\partial v_{L,j}^N}{\partial v_{L,j-1}^N} \frac{\partial v_{L,j-1}^N}{\partial W_{L}^{(p,k)}}, & \text{else}
\end{array} \right.
(5*)
\]

where \( f_p' \) is the derivative of the \( p-th \) element of \( v_{L,j} \) to \( f; v_{L-1,j}^N \) is the \( k-th \) feature of \( v_{L-1,j} \).

From Equation (5*), when the time step \( j \) \((j \in \{2, \ldots, n\})\) is fixed, for \( p \in \{1, \ldots, d_A\} \), the gradient flow from the interacted output features \( v_{L,j}^N \) can reach \( W_{L}^{(p,k)} \) through two ways: (i) directly reaches \( W_{L}^{(p,k)} \) \((v_{L,j}^N \rightarrow W_{L}^{(p,k)})\), (ii) Indirectly reach \( W_{L}^{(p,k)} \) through \( v_{L,j-1} \) \((v_{L,j}^N \rightarrow v_{L,j-1} \rightarrow W_{L}^{(p,k)})\); for \( j \in \{d_A + 1, \ldots, d\} \), although there is no the direct way of (i), the gradients from \( v_{L,j}^N \) can still flow into \( W_{L}^{(p,k)} \) through the indirect way of (ii).

In summary, for any parameter in \( W_L \), the gradients from the noised features can always flow into it and participate in the update of its value, and the conclusion is also true for the other parameters in \( U_L, b_L \). The reason that the gradients from the interacted features can be passed to each parameter in the main-branch RNN lies in the recurrent operation mode of the RNN. As a result, all parameters in each RNN layer can be influenced by the noised features during training. For the non-recurrent networks, ANI does not play the same role. In Section 3.2, we also leveraged simulation experiments to verify that the negative effects of noises to the trained RNN-ANI parameters can be effectively weakened under a proper noised proportion, which demonstrated that the influence of noised features involves all parameters in each RNN layer.

A.2. The equivalence of different selection schemes of noised features

[Theory] In theory, the only difference for each noised feature selection scheme is equivalent to a linear transformation of the main-branch RNN hidden states.

Assume that \( h_j \in \mathbb{R}^{d_A}, h_{A_j} \in \mathbb{R}^{d_A} \) (\( j \in \{1, \ldots, n\} \)) are the \( j-th \) hidden states of the main branch and the extra branch. The standard operation of ANI is as in Equation (1) and (2) of Section 2.2, and the form of \( y_j = \left(h_j^{(1)} + h_{A_j}^{(2)}, \ldots, h_j^{(d_A)} + h_{A_j}^{(d_A)}, h_j^{(d_A+1)}, \ldots, h_j^{(d_A)}\right)\). Now if we choose an interactive schemes

⁶Here we only take the standard RNN as the example, and the conclusion is also true for the variants of LSTM and GRU, because they are all recursive.
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Table A1. The standard results and average results of LSTM-ANI of Group I, II, III on WT103 validation and test sets.

| Group | I | II | III |
|-------|---|----|-----|
|       | LSTM-ANI | Standard | Average | Standard | Average | Standard | Average |
| Valid | 64.7 | 64.39 | 54.7 | 54.94 | 52.5 | 52.76 |
| Test  | 66.8 | 66.54 | 56.7 | 56.98 | 53.7 | 54.03 |

Table A2. The statistical Results of corpora of Penn Treebank (PTB), WikiText-2 (WTB) and WikiText-103 (WT103). The out of vocabulary (OoV) words will be replaced by <unk> during training and testing.

| Penn Treebank | WT-2 | WT-103 |
|---------------|------|--------|
| Articles      | Train | Val | Test | Train | Val | Test | Train | Val | Test |
| Tokens        | 887,521 | 70,390 | 78,669 | 2,088,628 | 217,646 | 245,569 | 103,227,021 | 217,646 | 245,569 |
| Vocab         | 10,000 | - | - | 33,278 | 33,278 | - | 267,735 | - | - |
| OoV           | 4.8% | - | - | 2.6% | - | - | 0.4% | - | - |

arbitrarily, whose result denoted as

\[ y'_j = (h^{(γ_1)}_j + h^{(1)}_{A_j}, ..., h^{(γ_d_A)}_j + h^{(d_A)}_{A_j}, h^{(γ_d_A + 1)}_j, ..., h^{(γ_d)}_j), \]

and \((γ_1, ..., γ_d)\) is a permutation of \((1, ..., d)\). Similar to Equation (1) in Section 2.2, \(y_j\) can be calculated as:

\[
y'_j = B \cdot h_j + P \cdot h_{A_j}, \quad (6*)
\]

\[ P = (I_{d_A}; 0)^T, \quad (7*)
\]

\[ B_{ij} = \begin{cases} 
1, & \text{if } j = γ_i \\
0, & \text{else} 
\end{cases} \quad (8*)
\]

Compare Equation (1 - 2) in Section 2.2 and Equation (6* - 8*), we can conclude that the only difference for each noised feature selection scheme is equivalent to a linear transformation \(B\) of the main-branch RNN hidden states \(h_j\). Similar to the inference of (Inan et al., 2016), by letting the main-brach RNN do the necessary linear mapping \(h_j \rightarrow B \cdot h_j\), different form of interactive feature selection can be converted to each other. Therefore, we can think that in the ideal situation, the RNN-ANI with fixed noised proportion \((d_A/d)\) can be automatically trained to the most appropriate form.

[Experiments] To verify the different noised feature selection are equivalent, we conduct experiments based on LSTM-ANI of Group I, II, III in Section 3.1 S2. We consider the noised features selection scheme in Equation (1 - 2) as the standard, and train multiple LSTM-ANI with different random noised feature selection schemes as in Equation (6* - 8*). We still use LSTM as the extra branch and set the noised proportion to 1/10, each result of different group language model on WT103 validation and test sets is the average of 3 runs. The results for each group are presented in Table A1. From Table A1, we can see that the difference between each standard and average results for each LSTM-ANI is indistinct, which prove that different noised feature selection schemes of ANI are equivalent.

A.3. Subspace projection method (Section 2.2)

The subspace projection method aims to enable the RNN before after the use of ANI to compare the overfitting degree with each other, which is the first problem to propose a structure-expanding regularization.

In (Mitchell, 1997), the definition of overfitting is: Given a hypothesis space \(H\), a hypothesis \(h \in H\) is said to overfit the training data if there exists some alternative hypothesis \(h' \in H\), such that \(h\) has smaller error than \(h'\) over the training examples, but \(h\) has a smaller error than \(h'\) over the entire distribution of instances.

Therefore, overfitting is a concept for a given hypothesis space. On a specific corpus, if we change the structure of a give network from \(A\) to \(B\), the corresponding hypothesis is transformed from \(H(A)\) to \(H(B)\). In this case, the performance of the two networks on the training validation sets cannot be used to judge the overfitting degree of them. The two model must be placed in the same hypothesis space to compare the training errors and validation errors. To this end, we develop the method of subspace projection to map the RNN before using ANI into a subspace of RNN-ANI, which is necessary for Section 3.1 S3 to verify the regularization effect of ANI.
B. Appendix II: Supplement for Section 3

B.1. Statistical Results of corpora of Penn Treebank (PTB), WikiText-2 (WTB) and WikiText-103 (WT103)

In experiments, we use three corpora: Penn Treebank (PTB), WikiText-2 (WTB) and WikiText-103 (WT103), whose statistical Results are in Table A2.

B.2. The Details of the four group LSTMs Language models in Section 3.1 S2

For each group of LSTM language models, the hidden size of each LSTM and the dimension of the word embeddings are set to 650 as in (Zaremba et al., 2014). We set the weight decay to $1.2 \times 10^{-6}$, and use mini-batch gradient descent, and train each model for 40 epochs with learning rate of 1, then divide the current learning rate by 2 for every 10 epochs until the 80th epoch. The parameters are initialized uniformly in $[-0.1, 0.1]$, the norm of the gradients are clipped at 5, the mini-batch is set to 128, and the model is unrolled for 70 steps. For facilitate the model training, we use adaptive Softmax (Grave et al., 2017).