ABSTRACT
Generalized zero-shot learning (GZSL) is one of the most realistic but challenging problems due to the partiality of the classifier to supervised classes, especially under the class-inductive instance-inductive (CIII) training setting, where testing data are not available. Instance-borrowing methods and synthesizing methods solve it to some extent with the help of testing semantics, but therefore neither can be used under CIII. Besides, the latter require the training process of a classifier after generating examples. In contrast, a novel non-transductive regularization under CIII called **Semantic Borrowing (SB)** for improving GZSL methods with compatibility metric learning is proposed in this paper, which not only can be used for training linear models, but also nonlinear ones such as artificial neural networks. This regularization item in the loss function borrows similar semantics in the training set, so that the classifier can model the relationship between the semantics of zero-shot and supervised classes more accurately during training. In practice, the information of semantics of unknown classes would not be available for training while this approach does NOT need it. Extensive experiments on GZSL benchmark datasets show that SB can reduce the partiality of the classifier to supervised classes and improve the performance of generalized zero-shot classification, surpassing inductive GZSL state of the arts.

CCS CONCEPTS
- Information systems → Clustering and classification.

KEYWORDS
Classification, inductive generalized zero-shot learning, semantic borrowing

1 INTRODUCTION
Classification has made great progress driven by the advancement of deep learning, but a large number of instances for each class are required, and the classifiers trained on the instances for training cannot classify instances of the classes that the previous instances don’t belong to. These challenges severely limit the application of these classification methods in practice. Many methods have been proposed to overcome these difficulties [20], including zero-shot learning [11, 12, 14] and generalized zero-shot learning (GZSL) [6, 21]. The semantic meaning of the label of a class can be defined by training examples of the class in traditional classification problems, but different from it, the semantic meaning of the label of an unseen class cannot be defined by training examples in GZSL. To solve this problem, a semantic space can be defined, in which each label of a seen or unseen class is identified uniquely. There are three training settings for a GZSL classifier. Class-transductive instance-inductive (CTII) setting allows the use of testing semantics during training, class-transductive instance-transductive (CTIT) setting also allows the use of unlabeled testing example features, and class-inductive instance-inductive (CIII) setting allows neither of these two. Their further descriptions can be found in [20]. The existing GZSL methods can be divided into six groups [20], namely correspondence, relationship, combination, projection, instance-borrowing and synthesizing methods. Due to the differences in the distributions of the seen and unseen classes, a GZSL classifier will suffer from the domain shift problem [9], which reduces the accuracy of generalized zero-shot learning [6]. Instance-borrowing methods [10] and synthesizing methods [17, 22, 25] solve this problem to some extent with the help of testing semantics, but therefore neither of them can be used under CIII [20] where testing data are invisible, and the latter always require the training process of a classifier after generating examples based on testing semantics.

In this paper, a non-transductive regularization is proposed to improve the compatibility metric learning used in GZSL methods under CIII. In the GZSL methods based on compatibility metric learning, the relationship between features and semantics, that is, compatibility, is learned through metric learning, and then the differences among the compatibilities between a testing feature and all semantic candidates in this metric space are determined, and finally, the semantic candidate corresponding to the testing example feature is determined accordingly, so that the class label of the testing feature can be obtained, thus achieving the goal of GZSL. Different from the process above, by additionally borrowing similar semantics in the training set, we can enable a classifier to model the relationship between the semantics of unseen and seen classes more accurately during training without the semantics of unseen classes, thereby reducing the partiality of the classifier to seen classes during testing to deal with the domain shift problem, as shown in Figure 1. The proposed regularization is named **Semantic Borrowing (SB)**.

The main contributions are highlighted as follows: 1) In practice, the semantics of unknown classes would not be available for training. So different from instance-borrowing methods and synthesizing ones, this approach utilizes neither semantics nor instances of unknown classes, totally under the strict but realistic CIII [20] training setting. 2) As a regularization, this approach not only can be used for training linear models, but also nonlinear ones such as artificial neural networks, improving GZSL methods with compatibility metric learning.

2 THE PROPOSED REGULARIZATION
SB is applied to the compatibility metric learning in GZSL methods. As mentioned earlier, GZSL with compatibility metric learning will learn the compatibilities between features and semantics through metric learning. At the same time, SB learns additionally the compatibility between each feature and the most similar semantic vector to the semantic vector corresponding to the feature. With the help
Figure 1: Illustration of the improvement of compatibilities by SB. The thickness of the line between a photo and text indicates the compatibility between them while the one between two texts indicates the semantic similarity between them. By borrowing similar semantics in the training set, we can enable a classifier to model more accurately the relationship between the semantics of unseen and seen classes during training without semantics of unseen classes.

of this information, the differences among the compatibilities between a testing feature and all semantic candidates in the learned metric space will be more accurate. In other words, the relationship between the semantics of unseen and seen classes is modeled more accurately by the classifier. SB is illustrated in the right panel of Figure 1.

The set of all seen classes is denoted as $B_\text{s}$ and the set of all unseen classes $B_\text{u}$, $B_\text{s} \cap B_\text{u} = \emptyset$, then the set of all classes $B = B_\text{s} \cup B_\text{u}$. For any class $b \in B$, there is a unique corresponding semantic vector $s \in \mathbb{R}^n$. The set of all semantic vectors is denoted as $S$, and the set of all semantic vectors of seen classes $S_\text{s}$, then the set of all seen-class examples $D_\text{s} = \{(f, s) \mid f \in F, s \in S_\text{s}\}$, where $F \subseteq \mathbb{R}^m$ is the set of all features of seen-class examples, and $F$ is the set of all features of examples. The set of all unseen-class examples is denoted as $D_\text{u}$, then GZSL learns a classifier on the training set $D_{\text{tr}} \subseteq \{(f, s) \mid f \in F_{\text{tr}}, s \in S_{\text{tr}}\} \subseteq D_\text{s}$ to obtain the classes of example features in testing sets $D_{\text{te-s}} \subseteq D_\text{s}$ and $D_{\text{u}}$, where $D_{\text{tr}} \cap D_{\text{te-s}} = \emptyset$.

### 2.1 Preparing Models for Regularization

The compatibilities between features and semantics form a metric space in which the compatibility between a feature and its corresponding semantic vector will be greater than those between the feature and other semantics. In order to learn such a space, we can use a linear model or a nonlinear one to fit it, but because they have different fitting capabilities due to the different complexities of a linear model and a nonlinear model, we need define different objectives to train them.

For the linear model, in order to adapt to its limited fitting ability, we can train a compatibility function $c : F \times S \rightarrow \mathbb{R}$ on the training dataset with the objective of symmetric structured joint embedding in the previous multi-modal structured learning methods [2, 3, 16]:

$$L_0^{(u)}(f_i, s_i; \theta) = L_f^{(u)}(f_i, s_i; \theta) + L_s^{(u)}(f_i, s_i; \theta),$$

where $(f_i, s_i) \in D_{\text{tr}}^{(u)} \subseteq D_{\text{tr}}$ and the two misclassification losses are:

$$L_f^{(u)}(f_i, s_i; \theta) = \sum_{s \in S_\text{tr}^{(u)}(s_i)} \max \{0, 1 + c(f_i, s; \theta) - c(f_i, s_i; \theta)\},$$

$$L_s^{(u)}(f_i, s_i; \theta) = \sum_{f \in F_\text{tr}^{(u)}(f_i)} \max \{0, 1 + c(f, s_i; \theta) - c(f_i, s_i; \theta)\},$$

where $S_\text{tr}^{(u)} \subseteq S_{\text{tr}}, F_\text{tr}^{(u)} \subseteq F_{\text{tr}}, |\cdot|$ indicates the cardinality of a set, $B \setminus A$ denotes the relative complement of $A$ in $B$.

For the nonlinear model, because of its strong fitting ability, we can use the MSE loss to train a compatibility function on the training set as in [18]. Therefore, $L_0^{(u)}$ in Eq. (1) becomes:

$$L_0^{(u)}(f_i, s_i; \theta) = \sum_{s \in S_\text{tr}^{(u)}(s_i)} c^2(f_i, s; \theta) + |c(f_i, s; \theta) - 1|^2.$$

### 2.2 Semantic Borrowing Regularization

After preparing the model that will be trained with Semantic Borrowing (SB), it is time to add SB regularization to its loss function. In order for the classifier to model the relationship between the semantics of unseen and seen classes more accurately during training, SB adds a new objective that borrows similar semantics in the training set. It is different from instance-borrowing methods, which borrow data in the testing set.

For the linear model above, the SB regularization is:

$$L_{\text{SB}}^{(u)}(f_i, s_i, s_j; \theta) = \sum_{s \in S_\text{tr}^{(u)}(s_i)} \max \{0, 1 + c(f_i, s; \theta) - c(f_i, s_j; \theta)\}.$$  

where $s_j \in S_{\text{tr}} \subseteq S_{\text{tr}}$ is the most similar semantic vector in the current second training subset $S_{\text{tr}}^{(2)}$ to $s_i$ in the current first training subset $S_{\text{tr}}^{(1)}$.

For the nonlinear model above, the SB regularization is formulated correspondingly as:

$$L_{\text{SB}}^{(u)}(f_i, s_i, s_j; \theta) = \sum_{s \in S_\text{tr}^{(u)}(s_i)} c^2(f_i, s; \theta) + |c(f_i, s; \theta) - 1|^2.$$  

Finally, the overall loss for a model trained with SB is:

$$L^{(1)}(\theta) = \sum_{(f_i, s_i) \in D_{\text{tr}}^{(2)}} L_0^{(2)}(f_i, s_i; \theta)$$

$$+ \alpha \sum_{(f_i, s_i) \in D_{\text{tr}}^{(2)} \setminus S_{\text{tr}}^{(2)}} \frac{L_{\text{SB}}^{(2)}(f_i, s_i, s_j; \theta) + \beta \|\theta\|_2}{C^{(2)+1}(s_i)},$$

where $t = 0, 1, 2, \ldots, \alpha \in (0, 1)$, $\beta$ controls weight decay, $C^{(1)} : S_{\text{tr}} \rightarrow S_{\text{tr}}^{(1)}$ is used to find similar semantics. By minimizing this loss, we can make the compatibility between a feature and the most
2.3 Semantic Similarities

When using SB to improve GZSL methods with compatibility metric learning, it is necessary to borrow the most similar semantic vector in the training set to each training semantic vector, which requires the calculation of the semantic similarity. Thanks to the process of determining the similarity in SB independent of the objective, in the case that the training semantics are equal-dimensional vectors of attributes, we can use the negative mean absolute error (-MAE) as the semantic similarity to make the semantic comparison more precise. Compared with the negative mean square error, cosine similarity and Ruzicka similarity [7], using -MAE can get better results on h and u in experiments. Therefore, the function for seeking similar semantics can be formulated as:

\[ C(a) \left( s_i \right) = \arg \min_{s \in S} \| s - s_i \|_1. \]  

(8)

2.4 Classification

By minimizing Eq. (7), we can obtain the compatibilities between features and semantics. Based on the learned compatibility function, a multi-class classifier \( M : F \rightarrow S \), that achieves the goal of GZSL can be formulated as follows:

\[ M(f) = \arg \max_{s \in S} c(f, s), \]  

(9)

where \( f \in F \). Then the class corresponding to \( M(f) \) is what we want.

3 EXPERIMENTS

3.1 Evaluation & Implementation

In order to evaluate SB, CUB [19] and SUN [15] are selected as the representatives of fine-grained benchmark datasets, and AWA1 [11], AWA2 [21] and aPY [8] as the representatives of coarse-grained benchmark datasets. The splits, semantics and evaluation metrics used in the comparison are proposed in [21], where semantics are class-level attributes. Different from [17], no additional semantics are used for CUB. If the length range of semantic vectors in a dataset is small, it will be scaled to be consistent with that in the other dataset. Following [4, 21, 22], example features are the 2048-dimensional top pooling units of a ResNet-101 pretrained on ImageNet-1K, without any preprocessing. Average per-class top-1 accuracies in % (T-1) are calculated as evaluation scores. The metrics \( u \) and \( s \) are T-1 of unseen and seen classes, respectively, and \( h \) is their harmonic mean [21]. \( u \) reflects the performance of a classifier for unseen classes, \( s \) reflects the performance for seen classes, and \( h \) indicates the comprehensive performance.

The experiments comprehensively evaluate SB with different models. The bilinear mapping [17] is selected as the representative of the linear model, and the multilayer perceptron (MLP) combination used in [18] as the representative of the nonlinear model. The combination consists of two MLPs with one hidden layer, and the numbers of hidden units are hyperparameters. The first MLP maps semantics into the feature space, and the second MLP maps the concatenations of features and mapped semantics into compatibilities. Each layer has a ReLU activation function, except for the last layer with a sigmoid activation function. The former model is optimized with minibatch SGD while the latter model is optimized with Adam.

3.2 Comparison with Inductive GZSL State of the Arts

There have been methods that can be used to solve the GZSL problem to some extent. Compared with them, we can see that SB can build new power for GZSL. In Table 1, linear models and nonlinear models trained with SB are both compared with state-of-the-art inductive GZSL methods.

Whether among linear or nonlinear models, it is easy to see that models trained with SB get the best \( h \) and \( u \), except in a few cases, but the scores are still almost equal to the best ones. It shows that they are less biased towards seen classes than those without SB and the comprehensive performance is also improved, as described in Section 1. It needs to be added that, unlike all other models in the table, which are trained under the CIII training setting where testing data are invisible, GAZSL and GMN use testing semantics to synthesize examples for unseen classes so as to learn the final classifier, so it is impossible for them to be used under CII. Therefore, they are NOT counterparts. AML and EDEM_ex are NOT, either. The comparison with all of these is added here for completeness. In fact, the use of SB in a synthesizing method with compatibility metric learning can be a future study, where SB will be used in non-CIII training settings.

3.3 Effectiveness

In order to verify the effectiveness of SB, an ablation study is conducted here. Table 2 demonstrates the comparison of models trained with and without SB. It shows SB improves \( h \) and \( u \) of both linear and non-linear models on both fine-grained and coarse-grained datasets, in some cases also improves \( s \), thanks to the more accurately modeled relationship between the semantics of unseen and seen classes with SB.

3.4 Effect

The effect of SB on the original method is affected by \( \alpha \) in Eq. (7). By evaluating models trained with different \( \alpha \), the way SB takes effect can be more clear. For this, a set of linear models are trained with different \( \alpha \) on CUB. Figure 2 shows the evaluation results of six representative values of \( \alpha \). Combined with Table 2, it can be seen that the models are worse than those trained without SB when \( \alpha \geq 1 \). It is expected because the compatibility between each feature and its semantically similar semantic vector is learned additionally with SB, so that the relationship between the semantics of unseen and seen classes is modeled more accurately, which improves the performance of the GZSL classifier, but when each compatibility of this kind is greater than or equal to the compatibility between the feature and its corresponding semantic vector, the relationship modeling becomes worse. In addition, we can observe that the model obtains the best \( h \) and \( s \) when \( \alpha = 0.01 \) and the best \( h \) and \( u \) when \( \alpha = 0.1 \). On the both sides, the performance of the model decreases. It shows again that modeling a too large or too small compatibility between each feature and its semantically similar semantic vector
Table 1: Comparison of models trained with and without SB. Their results are taken from the papers. The results of linear models are listed in the upper half of the table, and the results of nonlinear models in the lower half. In each half, the methods above Trained with SB are counterparts, and the methods below Trained with SB are NOT counterparts. h reflects the comprehensive performance.

| Method        | CUB          | SUN          | AWA1        | AWA2        | pPY          |
|---------------|--------------|--------------|-------------|-------------|--------------|
|               | u | s | h | u | s | h | u | s | h | u | s | h | u | s | h | u | s | h |
| DAP [11]      | 1.7 | 67.9 | 3.5 | 4.2 | 25.1 | 7.2 | 0.0 | 88.7 | 0.0 | 0.0 | 84.7 | 0.0 | 4.8 | 78.3 | 9.0 |
| LAF [11]      | 0.2 | 72.8 | 0.4 | 1.0 | 37.8 | 1.3 | 2.1 | 78.2 | 4.1 | 0.9 | 87.6 | 1.8 | 5.7 | 65.6 | 10.4 |
| CONSE [13]    | 1.6 | 72.2 | 3.1 | 6.8 | 39.9 | 11.6 | 0.4 | 88.6 | 0.8 | 0.5 | 90.6 | 1.0 | 0.0 | 91.2 | 0.0 |
| ALE [1]       | 23.1 | 62.8 | 34.4 | 21.8 | 33.1 | 26.3 | 16.8 | 76.1 | 27.5 | 14.0 | 81.8 | 23.9 | 4.6 | 73.7 | 8.7 |
| SYNC [5]      | 11.5 | 70.9 | 19.8 | 7.9 | 43.3 | 13.4 | 8.9 | 87.3 | 16.2 | 10.0 | 90.5 | 15.0 | 7.4 | 66.3 | 13.3 |
| Trained with SB | 29.1 | 59.8 | 39.1 | 22.8 | 30.7 | 26.2 | 21.8 | 86.1 | 34.8 | 17.2 | 89.2 | 28.8 | 18.2 | 73.0 | 29.1 |
| AMF [10]      | 25.7 | 66.6 | 37.1 | 20.0 | 38.2 | 28.3 | 11.8 | 89.6 | 20.8 | - | - | - | 12.6 | 74.3 | 21.5 |
| RN [18]       | 38.1 | 61.4 | 47.0 | - | - | - | 31.4 | 91.3 | 46.7 | 30.0 | 93.4 | 45.3 | - | - | - |
| DEM [14]      | 19.6 | 57.9 | 29.2 | 20.5 | 34.3 | 25.6 | 32.5 | 84.7 | 47.3 | 30.5 | 86.4 | 45.1 | 11.1 | 75.1 | 19.4 |
| EDDEM [21]    | 21.0 | 66.0 | 31.9 | 22.1 | 35.6 | 27.3 | 36.9 | 90.6 | 52.4 | 35.2 | 93.0 | 51.1 | 7.8 | 73.5 | 14.1 |
| Trained with SB | 41.7 | 64.2 | 50.6 | 23.1 | 42.9 | 30.0 | 36.3 | 86.7 | 51.4 | 34.8 | 89.2 | 50.1 | 16.4 | 86.9 | 27.2 |
| "GMN [17]    | 53.7 | 61.4 | 41.8 | 22.1 | 39.5 | 28.3 | 29.6 | 84.2 | 43.8 | - | - | - | 14.2 | 78.6 | 24.9 |
| "GEM [17]    | 58.4 | 54.3 | 51.2 | 53.2 | 33.8 | 40.7 | 61.1 | 71.3 | 65.8 | - | - | - | - | - | - |
| "EDDEM_ex [21] | 54.0 | 62.9 | 58.1 | 47.2 | 38.5 | 42.4 | 71.4 | 90.1 | 79.7 | 68.4 | 93.2 | 78.9 | 29.8 | 79.4 | 43.3 |

Table 2: Comparison of models trained with and without SB.

| Model        | CUB          | AWA1        |
|--------------|--------------|-------------|
|              | u | s | h | u | s | h |
| Linear       | 27.2 | 59.9 | 37.4 | 18.0 | 84.3 | 29.6 |
| Linear+SB    | 20.1 | 59.8 | 39.1 | 21.8 | 86.1 | 34.8 |
| Nonlinear    | 40.0 | 63.0 | 48.9 | 32.3 | 87.9 | 47.4 |
| Nonlinear+SB | 43.7 | 64.2 | 56.6 | 36.5 | 86.7 | 51.4 |

Figure 2: Analysis of the influence of α on u, s and h scores of a linear model trained with SB on CUB.

4 CONCLUSION

In this work, non-transductive semantic borrowing regularization is proposed to improve GZSL methods with compatibility metric learning under CIL. Extensive evaluation of representative models trained on representative GZSL benchmark datasets with the proposed regularization has shown that it can improve the performance of generalized zero-shot classification, surpassing inductive GZSL state of the arts.

REFERENCES

[1] Zeynep Akata, Florent Perronnin, Zaid Harchaoui, and Cordelia Schmid. 2013. Label-embedding for attribute-based classification. In Proceedings of the IEEE conference on computer vision and pattern recognition. 819–826.
[2] Zeynep Akata, Florent Perronnin, Zaid Harchaoui, and Cordelia Schmid. 2015. Label-embedding for image classification. IEEE transactions on pattern analysis and machine intelligence, 37 (7) (2015), 1425–1438.
[3] Zeynep Akata, Scott Reed, Daniel Walter, Honglak Lee, and Bernt Schiele. 2015. Evaluation of output embeddings for fine-grained image classification. In Proceedings of the IEEE conference on computer vision and pattern recognition. 2927–2936.
[4] Maxime Bucher, Stéphane Herbin, and Frédéric Jurie. 2017. Generating visual representations for zero-shot classification. In Proceedings of the IEEE International Conference on Computer Vision Workshops. 2666–2673.
[5] Soravit changpinyo, Wei-Lun Chao, Boqing Gong, and Fei Sha. 2016. Synthesized classifiers for zero-shot learning. In Proceedings of the IEEE conference on computer vision and pattern recognition. 5327–5336.
[6] Wei-Lun Chao, Soravit Changpinyo, Boqing Gong, and Fei Sha. 2016. An empirical study and analysis of generalized zero-shot learning for object recognition in the wild. In European conference on computer vision. Springer, 52–68.
[7] Michel Marie Deza and Elena Deza. 2009. Encyclopedia of distances. In Encyclopedia of distances. Springer, 1–583.
[8] Ali Farhadi, Ian Endres, Derek Hoiem, and David Forsyth. 2009. Describing objects by their attributes. In 2009 IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 1778–1785.
[9] Yanwei Fu, Timothy M Hospedales, Tao Xiang, and Shaogang Gong. 2015. Transductive multi-view zero-shot learning. IEEE transactions on pattern analysis and machine intelligence, 37, 11 (2015), 2332–2345.
[10] Huajie Jiang, Ruiping Wang, Shiguang Shan, and Xilin Chen. 2019. Adaptive metric learning for zero-shot recognition. IEEE Signal Processing Letters, 26, 9 (2019), 1270–1274.
[11] C. H. Lampert, H. Nickisch, and S. Harmeling. 2009. Learning To Detect Unseen Object Classes by Between-Class Attribute Transfer. In IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR).
[12] Hugo Larochelle, Dumitru Erhan, and Yoshua Bengio. 2008. Zero-data learning of new tasks.. In AAAI, Vol. 1. 3.
[13] Mohammad Norouzi, Tomas Mikolov, Samy Bengio, Yoram Singer, Jonathon Shlens, Andrea Frome, Greg S Corrado, and Jeffrey Dean. 2013. Zero-shot learning by convex combination of semantic embeddings. arXiv preprint arXiv:1312.5650 (2013).
[14] Mark M Palatucci, Dean A Pomerleau, Geoffrey E Hinton, and Tom Mitchell. 2009. Zero-shot learning with semantic output codes. (2009).
[15] Genevieve Patterson and James Hayes. 2012. Sun attribute database: Discovering, annotating, and recognizing scene attributes. In 2012 IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2751–2758.
[16] Scott Reed, Zeynep Akata, Honglak Lee, and Bernt Schiele. 2016. Learning deep representations of fine-grained visual descriptions. In Proceedings of the IEEE conference on computer vision and pattern recognition. 49–58.
[17] Mert Bulent Sarıyıldız and Ramazan Gokberk Cimbir. 2019. Gradient matching generative networks for zero-shot learning. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2688–2700.
[18] Flood Sung, Yongxin Yang, Li Zhang, Tao Xiang, Philip HS Torr, and Timothy M Hospedales. 2018. Learning to compare: Relation network for few-shot learning. In Proceedings of the IEEE conference on computer vision and pattern recognition. 1199–1208.
[19] Catherine Wah, Steve Branson, Peter Welinder, Pietro Perona, and Serge Belongie. 2011. The caltech-ucsd birds-200-2011 dataset. (2011).

[20] W. Wei, V. W. Zheng, Y. Han, and C. Miao. 2019. A Survey of Zero-Shot Learning: Settings, Methods, and Applications. ACM Transactions on Intelligent Systems and Technology 10, 2 (2019), 1–37.

[21] Yongqin Xian, Christoph H Lampert, Bernt Schiele, and Zeynep Akata. 2018. Zero-shot learning—a comprehensive evaluation of the good, the bad and the ugly. IEEE transactions on pattern analysis and machine intelligence 41, 9 (2018), 2251–2265.

[22] Yongqin Xian, Tobias Lorenz, Bernt Schiele, and Zeynep Akata. 2018. Feature generating networks for zero-shot learning. In Proceedings of the IEEE conference on computer vision and pattern recognition. 5542–5551.

[23] Lei Zhang, Peng Wang, Lingqiao Liu, Chunhua Shen, Wei Wei, Yanning Zhang, and Anton Van Den Hengel. 2020. Towards effective deep embedding for zero-shot learning. IEEE Transactions on Circuits and Systems for Video Technology 30, 9 (2020), 2843–2852.

[24] Li Zhang, Tao Xiang, and Shaogang Gong. 2017. Learning a deep embedding model for zero-shot learning. In Proceedings of the IEEE conference on computer vision and pattern recognition. 2021–2030.

[25] Yizhe Zhu, Mohamed Elhoseiny, Binglechen Liu, Xi Peng, and Ahmed Elgammal. 2018. A generative adversarial approach for zero-shot learning from noisy texts. In Proceedings of the IEEE conference on computer vision and pattern recognition. 1004–1013.