Attribute Prediction in Fashion Clothes

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AI Competition description

How to judge the styles of clothes ？

we concentrate on the following aspects to improve the recognition performance:

1: Data argumentation

2: Transfer learning

3: Model fusion

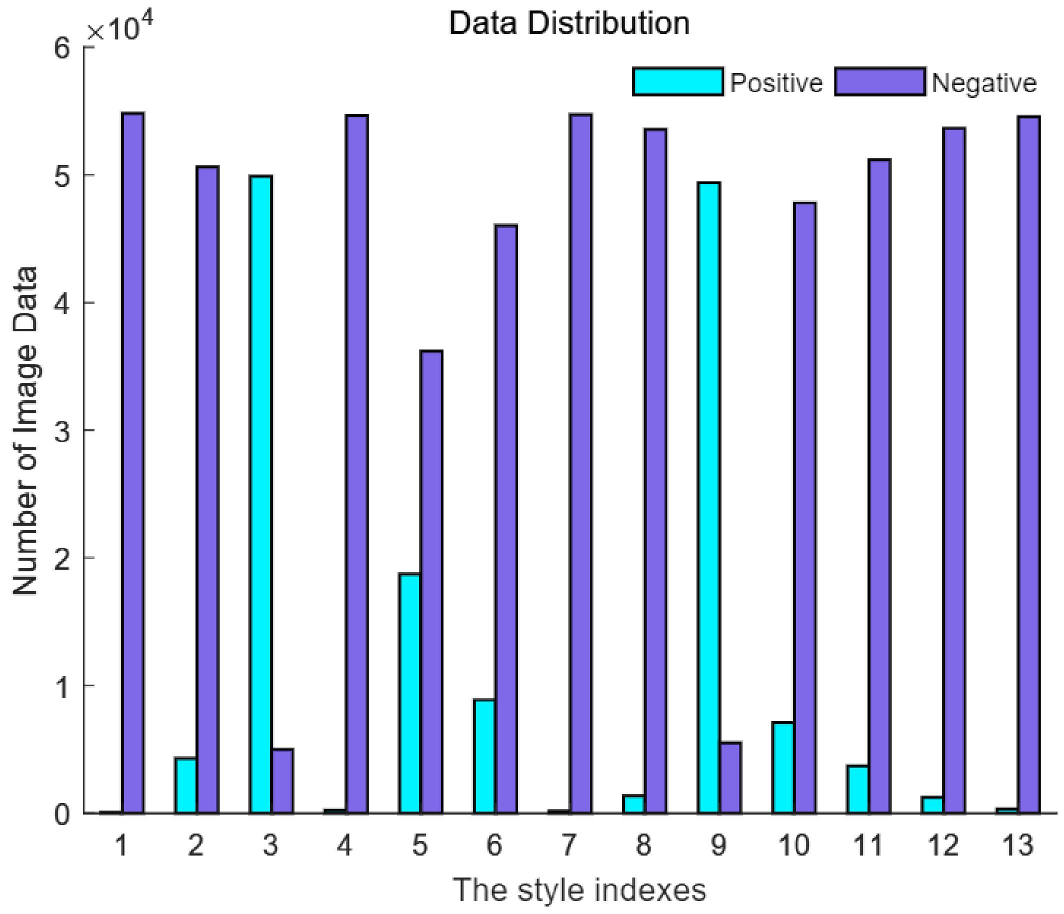
4: The style relationship

Sports	British
Casua	Girl
Office Lady	Lady
Japanese	Minimalist
Korean	Natural
Western	Punk
Ethnic	

Challenges

Imbalance data distribution

Distribution of the training and validation dataset. It is obviously shown that the class distribution is seriously imbalance. Taking style index 1(运动) as example, there are 104 positive samples while 54804 negative samples in the dataset.



Challenges

Posture

Noise sample

Background

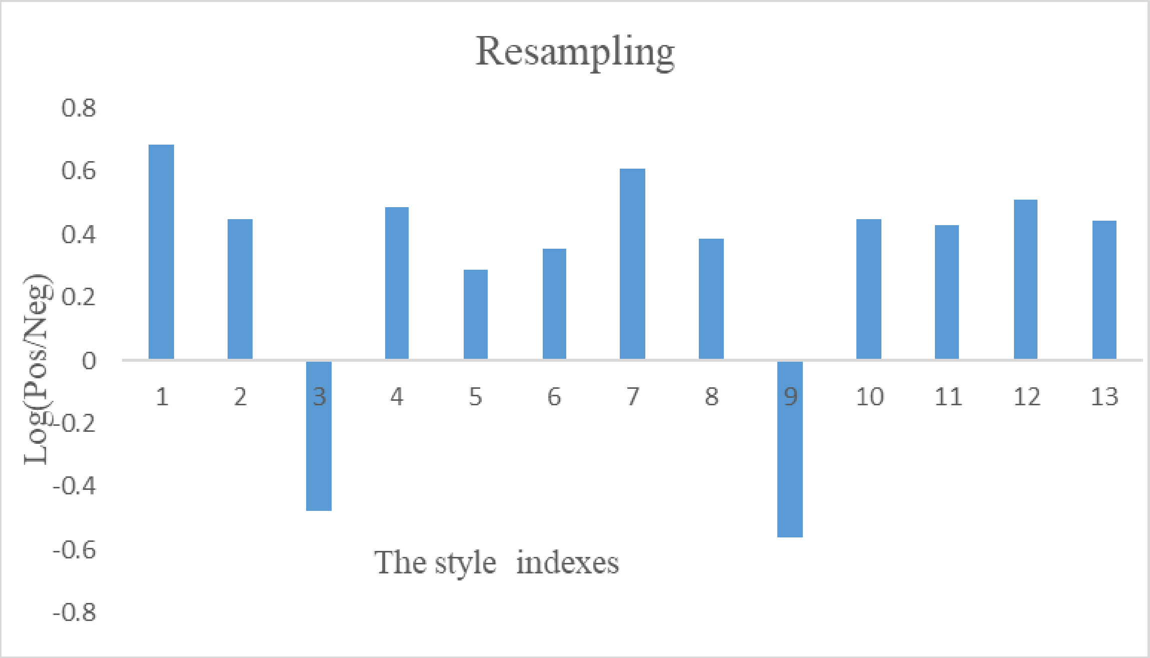
Error labeling

(not belong to Sports)

AI Data argumentation

Resampling the training set

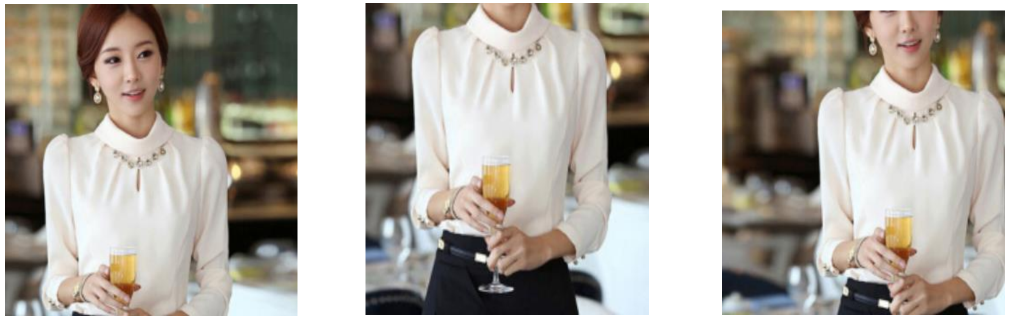
To avoid over-fitting, we resampled the training set to make sure each training batch contains proper positive samples. Moreover, we undersampled negative samples for classes 1, 2, 4, 7, 8, 10, 11, 12, 13 and kept the original proportion for classes 3, 5, 6, 9. The core idea of this opertion is trying to make a balance on improving the pos-neg proportion and maintaining the original data distribution.



Data argumentation

Three ways for data argumentation

Input image



Random Croping

Random Croping

Random Erasing

Random Croping +Random Erasing+ Random Rotating

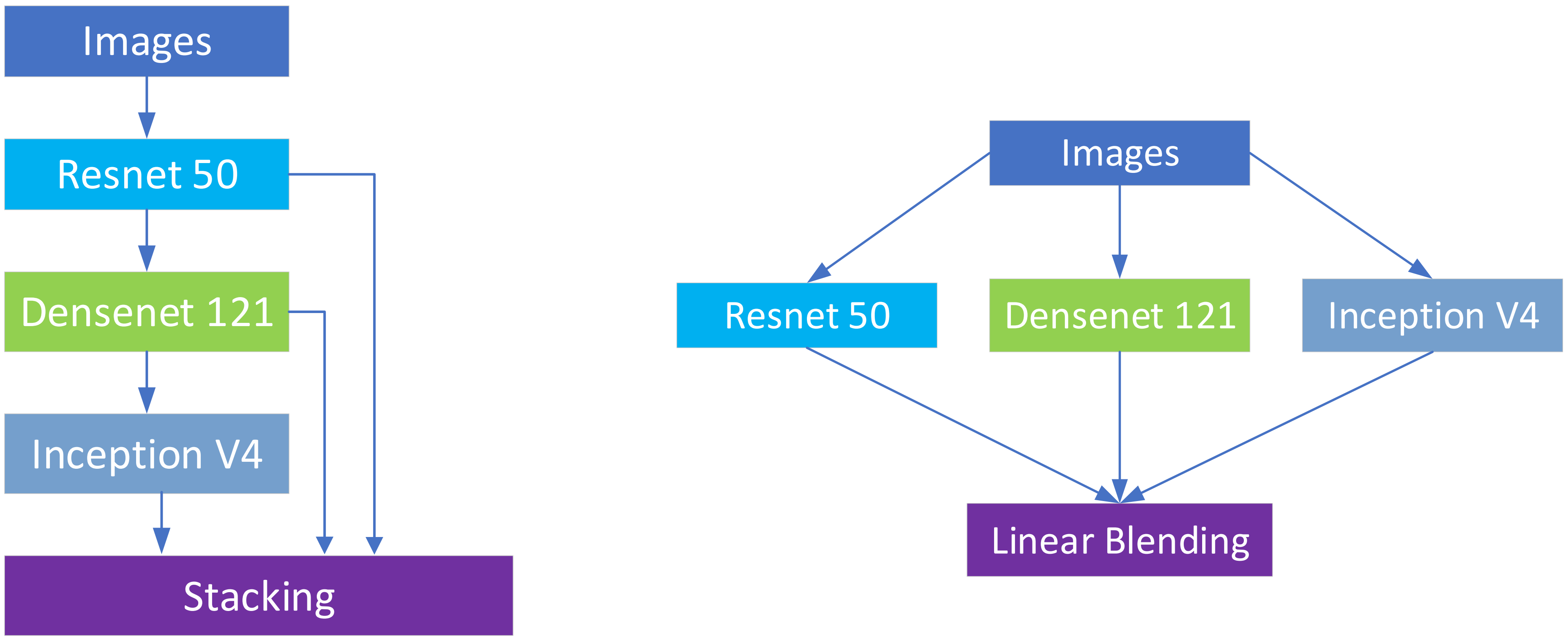
Network architecture

Summary of the 13 style indexes provided by the JDAIfashion dataset.

Index.	**Style.**	**Index.**	**Styles.**
1	Sports	8	Girl
2	Casual	9	Lady
3	Office lady	10	Minimalist
4	Japanese	11	Natural
5	Korean	12	Punk
6	Western	13	Ethnic
7	British		

AI Network architecture

Comparison of stacking and linear blending method.



Network architecture

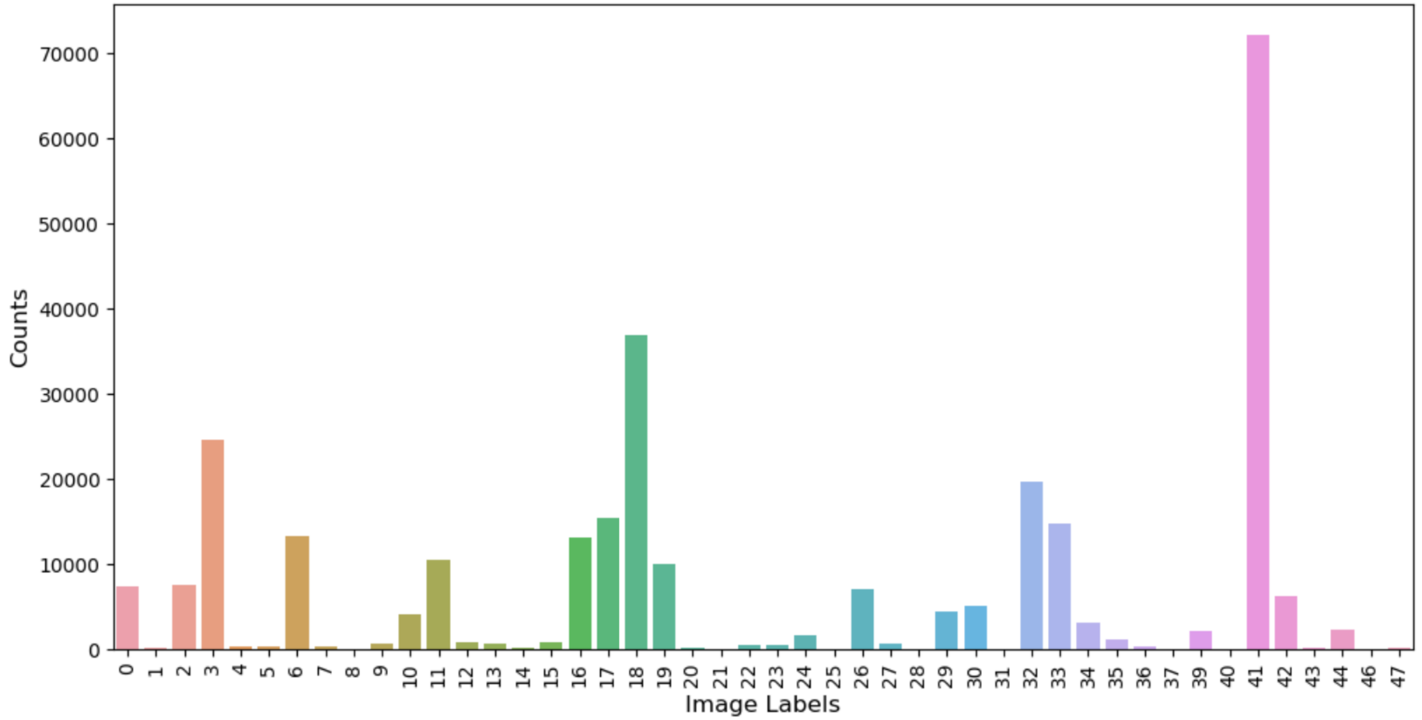
The base model and linear blending method result

Network	1	2	3	4	5	6	7
Resnet50	0.16	0.62	0.97	0.35	0.67	0.65	0.16
Densenet121	0.13	0.65	0.98	0.35	0.68	0.65	0.16
Inception-v4	0.14	0.64	0.97	0.35	0.67	0.66	0.17
Model Fusion	0.18	0.67	0.98	0.37	0.70	0.70	0.17

Network	8	9	10	11	12	13	Mean
Resnet50	0.42	0.97	0.63	0.75	0.42	0.33	0.55
Densenet121	0.44	0.97	0.63	0.75	0.44	0.31	0.55
Inception-v4	0.42	0.96	0.64	0.75	0.40	0.33	0,55
Model Fusion	0.45	0.97	0.64	0.77	0.45	0.33	0.57

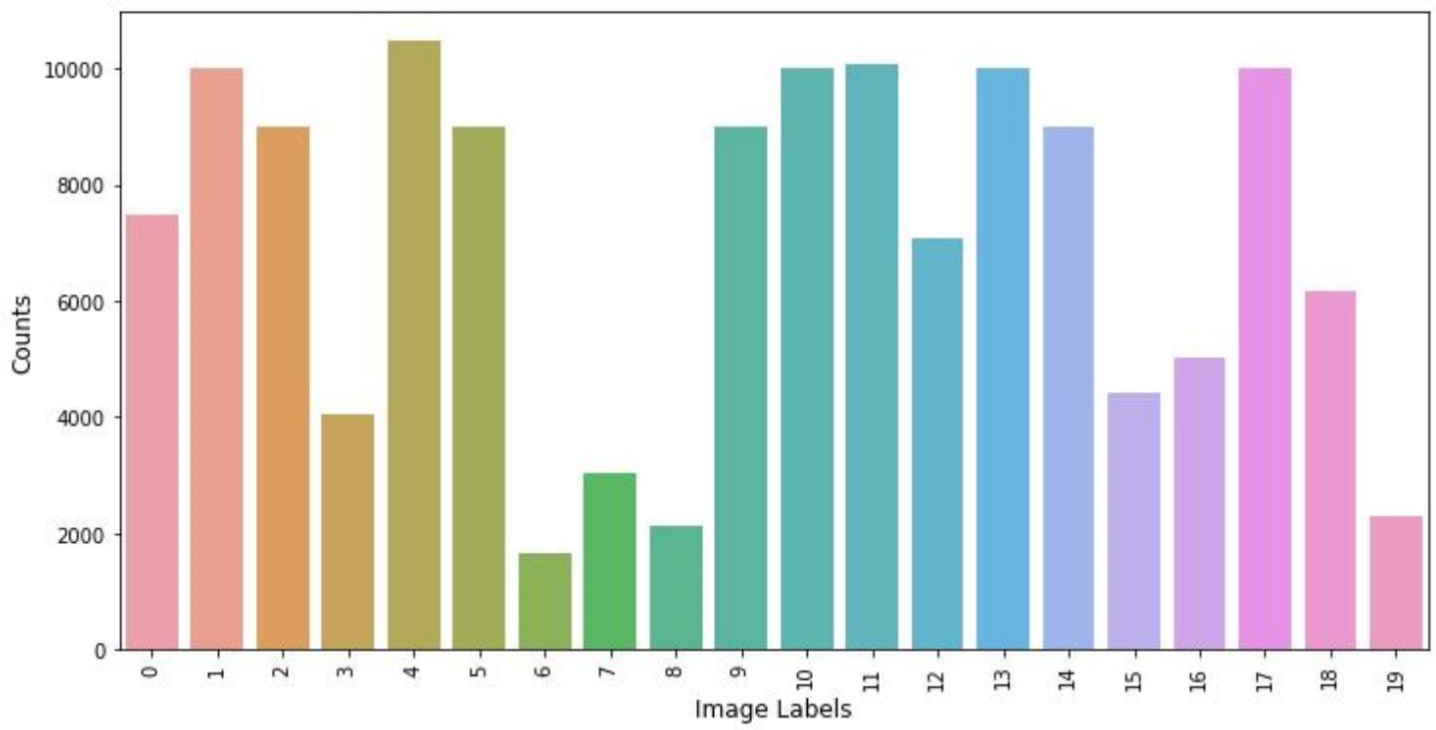
AI Transfer learning

Since there is a huge gap between ImageNet dataset and JDAIfashion dataset, using ImageNet pretrained model to initialize the weights to help the style recognition may get sub-opt. Hence, we pre-train our base model on **DeepFashion** dataset, which is a big clothing fashion dataset and have more closely data distribution with JDAIfashion dataset.



AI Transfer learning

DeepFashion contains over 800,000 diverse fashion images ranging from well-posed shop images to unconstrained consumer photos. Each image in this dataset is labeled with around 50 categories, 1000 descriptive attributes, bounding box and clothing landmarks. Our pre-training task concentrates on classifying 50 clothes attributes. To get better pre-trained model, we **cleaned the dataset** and selected **20 attributes** with more balanced data distribution.



AI Transfer learning

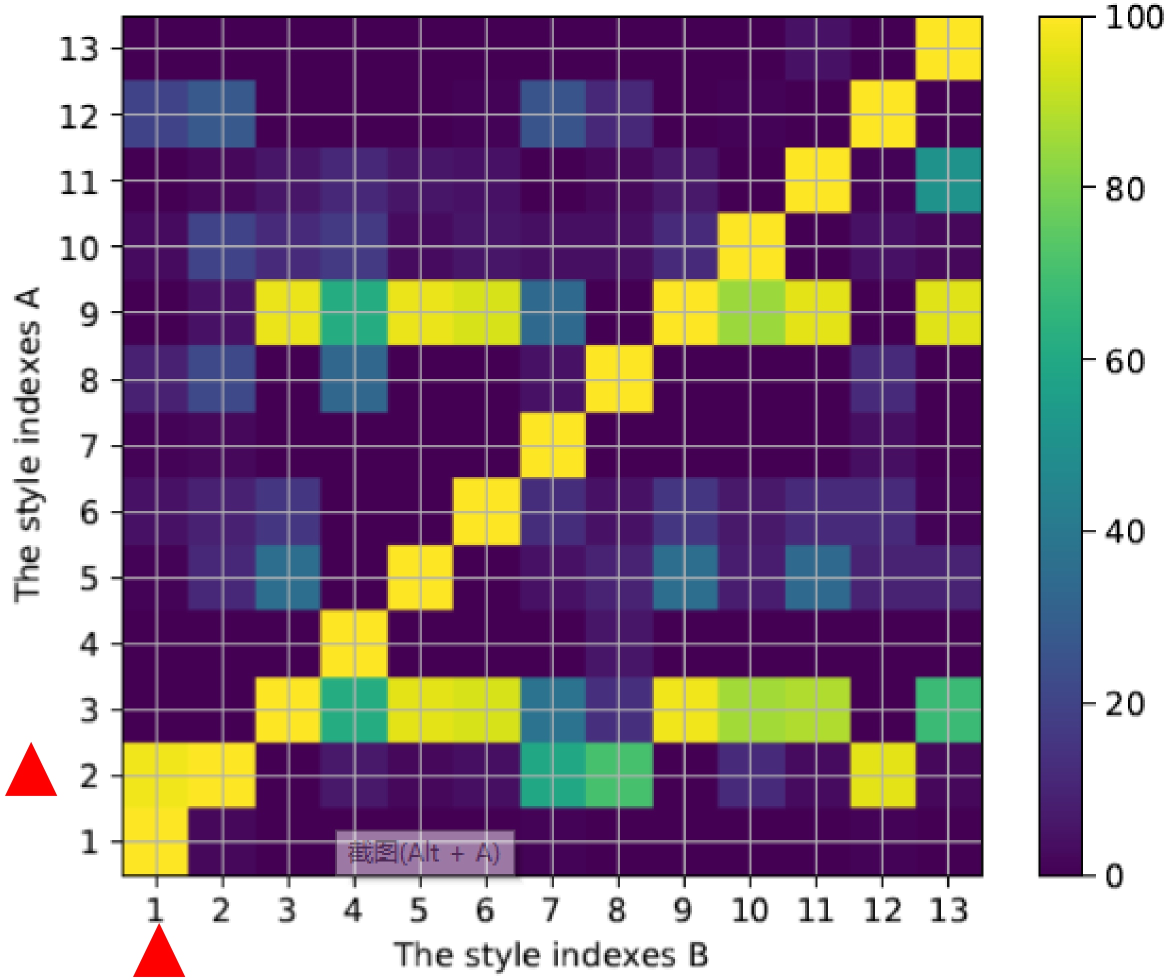
Performance of using transfer learning for different styles.

Approach	1	2	3	4	5	6	7
Model Fusion	0.18	0.67	0.98	0.37	0.70	0.70	0.17
Transfer Learning	0.22	0.69	0.98	0.42	0.72	0.73	0.23

Approach	8	9	10	11	12	13	Mean
Model Fusion	0.45	0.97	0.64	0.77	0.45	0.33	0.57
Transfer Learning	0.47	0.97	0.66	0.79	0.47	0.35	0.59

AI Styles relationship

The conditional probability of style index A when style index B happened. The indexes are declared in Table I. For example, if the clothes belongs to style index 1 (Sports), it may belongs to style index 2 (Casual) with a probability of 95%.



AI Styles relationship

We analyzed the conditional probability of the given labels with Eqn.1.

$$P(A|B) = \frac{N(A \bigcap B)}{N(B)} \qquad (1)$$

Where $N(A \bigcap B)$ means the number of images simultaneously belonging to style A and B. N (B) means the number of images belonging to style B. Since we have processed each style individually, we applied the styles relationship (conditional probability) using Eqn.2.

$$P_{final}(A) = \alpha \cdot P(A) + \sum_{i \in M} \beta_i \cdot P(A|B_i) \qquad (2)$$

where α and β_i are the hyper-parameters to balance the contribution of styles relationship. P (A) means the probability calculated by our convolutional neural network. M is the candidate set that our network predict to be positive $(B_i \neq A)$. If the network predicts all the styles B_i as positive with confidence score 0, then the final confidence score of style A is: $P_{final}(A) = P(A)$

Experiment result

We adopted cross-validation method to evaluate the individual models and the fusion results. Specifically, we split 43926 images for training and 10981 for validation.

Data Augmentation	–	Yes	Yes	Yes	Yes
Transfer learning	–	–	Yes	Yes	Yes
Cost-Sensitive	–	–	–	Yes	Yes
Styles relationship	–	–	–	–	Yes
Mean F2-score	0.44	0.57	0.59	0.60	0.63

AI CONCLUSION

In this paper, we introduce our proposed method for clothing style classification in JD AI Fashion-Challenge. Our method dealt with the problem from the aspects of data argumentation, network structure, transfer learning and cost sensitive learning. Besides, we investigated the styles relationship for the post processing. With the proposed approach, we achieved 0.6524 F2-score on the testing set, which is the 3rd place on the leaderboard.

AI Extension

1、detection and recognition (image-level detector)

Zhou B, Khosla A, Lapedriza A, et al. Learning deep features for discriminative localization[C]//Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2016: 2921-2929.

2、cost-sensitive learning (interclass distance)

3、joint multi-task learning

4、bottom-up feature fusion

Lin T Y, Dollár P, Girshick R B, et al. Feature Pyramid Networks for Object Detection[C]//CVPR. 2017, 1(2): 3.

END

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