

PETS-SWINF: A regression method that considers images with metadata based Neural Network for pawpularity prediction on 2021 Kaggle Competition "PetFinder.my"

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Abstract

Millions of stray animals suffer on the streets or are euthanized in shelters every day around the world. In order to better adopt stray animals, scoring the pawpularity (cuteness) of stray animals is very important, but evaluating the pawpularity of animals is a very labor-intensive thing. Consequently, there has been an urgent surge of interest to develop an algorithm that scores pawpularity of animals. However, the dataset in Kaggle not only has images, but also metadata describing images. Most methods basically focus on the most advanced image regression methods in recent years, but there is no good method to deal with the metadata of images. To address the above challenges, the paper proposes an image regression model called PETS-SWINF that considers metadata of the images. Our results based on a dataset of Kaggle competition, "PetFinder.my", show that PETS-SWINF has an advantage over only based images models. Our results shows that the RMSE loss of the proposed model on the test dataset is **17.71876** but 17.76449 without metadata. The advantage of the proposed method is that PETS-SWINF can consider both low-order and high-order features of metadata, and adaptively adjust the weights of the image model and the metadata model. The performance is promising as our leadboard score is ranked 18 out of 3537 teams for 2021 Kaggle competition on the challenge "PetFinder.my".

Keywords: Deep learning, Factorization machines, Recommender systems, Fusion, Image regression, Metadata

1. Introduction

With the development of computers and the application of machine learning, computer vision is one of the hottest research fields in the data science world [1]. Image regression [2] is different from image classification in that it requires the model to give a continuous predicted value rather than a discrete value. There are few researches on image regression, but in recent years the problem of "facial beauty prediction" (FBP) has been attracting a lot of interest in the pattern recognition and machining learning communities [3, 4, 5, 6], and its basic research has contributed to the rapid development of the plastic surgery and cosmetic industry, such as cosmetic recommendations, aesthetic surgical planning, facial postural analysis, and facial beautification [7, 8].

But apart from human faces, cute animals also attract people's attention, which is why more and more people like to keep pets. At the same time, millions of stray animals suffer on the streets or are euthanized in shelters every day around the world [9, 10]. It would

be great if more stray animals can be adopted by caring people as their pets. So if there is an algorithm that scores images of animals based on "facial beauty predictions", we are able to accurately determine a pet photo's attraction and suggest improvements to give these rescued animals a higher chance of loving homes.

The objective of Pawpularity Contest¹ is to help us better understand, analyze, and enhance the pet photos. This would not only help the animals find loving homes faster, but also free up shelter and rescuer resources to assist more needy animals. The situation has become more dire due to the Coronavirus disease, as shelters are overwhelmed with animals and resources are limited. In this competition, we analyze raw images and metadata to predict the "Pawpularity" (cuteness, related to click-through rate) of stray animals. We train and test our model on PetFinder.my's² thousands of pet profiles, as shown in Fig. 1.

Literature Review: Image regression differs from image recognition models as a continuous predictive output is required, instead of a discrete one. This category of tasks are rare, where most of them target at "human facial beauty prediction" such as [8] and

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¹<https://www.kaggle.com/c/petfinder-pawpularity-score/>

²<https://www.petfinder.my/>

[11]. L Xu et al. proposed a new network framework, Classification and Regression Network (CRNet) [12], which uses different branches to handle classification and regression tasks simultaneously. Adapting rich deep features to facial beauty prediction has been applied as feature extraction techniques reported in [13] and [14]. A residue-in-residual (RIR) structure is proposed to make gradient flow pass deeper and establish a better path for information transmission in “Deep Learning for Facial Beauty Prediction” [15]. J Gan et al. propose a lighted deep convolution neural network (LDCNN) based on the Inception model of Googlenet and max-feature-max activation Layer can extract multi-scale features of images, obtain compressed representation, and reduce parameters [16]. Moreover, score-level fusion methods are proved feasible in recognizing and evaluating animal facial characteristics [17].

Most methods focus on the most advanced image regression methods in recent years, such as Swin-Transformer [18], EfficientNet [19]. but there is few good methods to deal with the metadata of images (some abstract features to describe images, details in Appendix A). To address the above challenges, we made two heads for the model, one was predicting pawpularity through images while the other auxiliary head tried to predict pawpularity through metadata. Through the performance on the validation set to perform the fusion of the two models, we found that the fusion of the metadata model can improve accuracy of prediction. The main contributions of this article are two-fold: (i) We propose an image regression model called PETS-SWINF that considers metadata of the images. (ii) The model we propose can consider both low-order and high-order features of metadata, and adaptively adjust the weights of the image and the metadata model. The proposed method win the in Kaggle competition called 2021 PetFinder.my (currently ranked **18/3537**).

The rest of the manuscript is organized as follows: Section 2 briefly introduces the proposed PETS-SWINF. The data analysis is presented in Section 3. Results and disussion of the proposed PETS-SWINF are presented in Section 4. Finally, Section 5 concludes the work.

2. Method

This problem is essentially a regression problem through images and metadata. Here we use two single-task learning to regress the images and metadata separately, and then give the both models weights to integrate the model. We use Swin Transformer to model the image regression [18]. Metadata model is inspired by the idea of DeepFM [20] for regression. Then the weights of the two models are obtained based on the loss of the validation set, and the fusion is carried

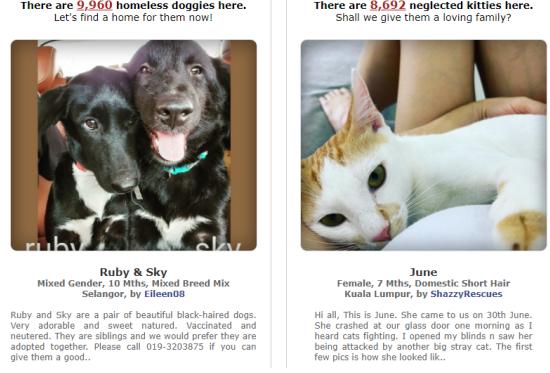


Fig. 1. Petfinder pet profiles (<https://www.petfinder.my/>).

out. There are three fundamental steps involved in the proposed regression system- images regression, metadata regression and parallelly fusion. These steps are shown in Fig. 2.

2.1. Metadata regression

The flowchart of the metadata model is as shown in Fig. 2 (a). We aim to learn both low-order and high-order features of the metadata. Since metadata have semantic information, we use NLP trained model embedding (here we use Glove [21]) instead of processing the original metadata directly. The reason is that the original metadata (0 or 1) are not sufficient resulting in the failure to restore the real input information well if dealing with original metadata. Given the sparsity of the original data and in order to reduce the latter computational cost, MLP is used for dimensionality reduction, and each feature is normalized to obtain low-level features. Next, each low-level feature is dotted product with all other low-level features,

$$F_{high} = F_{low} \cdot F_{low}^T, \quad (1)$$

where $F_{low} \in R^{M \times D}$ is the representation of the lower-order features (M is the number of the metadata, D is the reduced dimensionality). Then we flatten the high-order features F_{high} , and multiple nonlinear activation functions are applied to the high-order features. At last the high-order features and low-order features are concatenated together.

The reason for concatenation is that it's not clear whether low-level features or high-level features determine the final regression value. This depends on the target problem. One of the advantages of this network is that model can learn high-order features and low-order features based on the characteristics of the dataset. If the two low-order features are very similar, then the corresponding high-order feature is close to 1. The similarity here takes into account the cosine similarity of the Glove model. The high-order features are acted by the activation function and can have the ability to the stronger non-linear expression. After

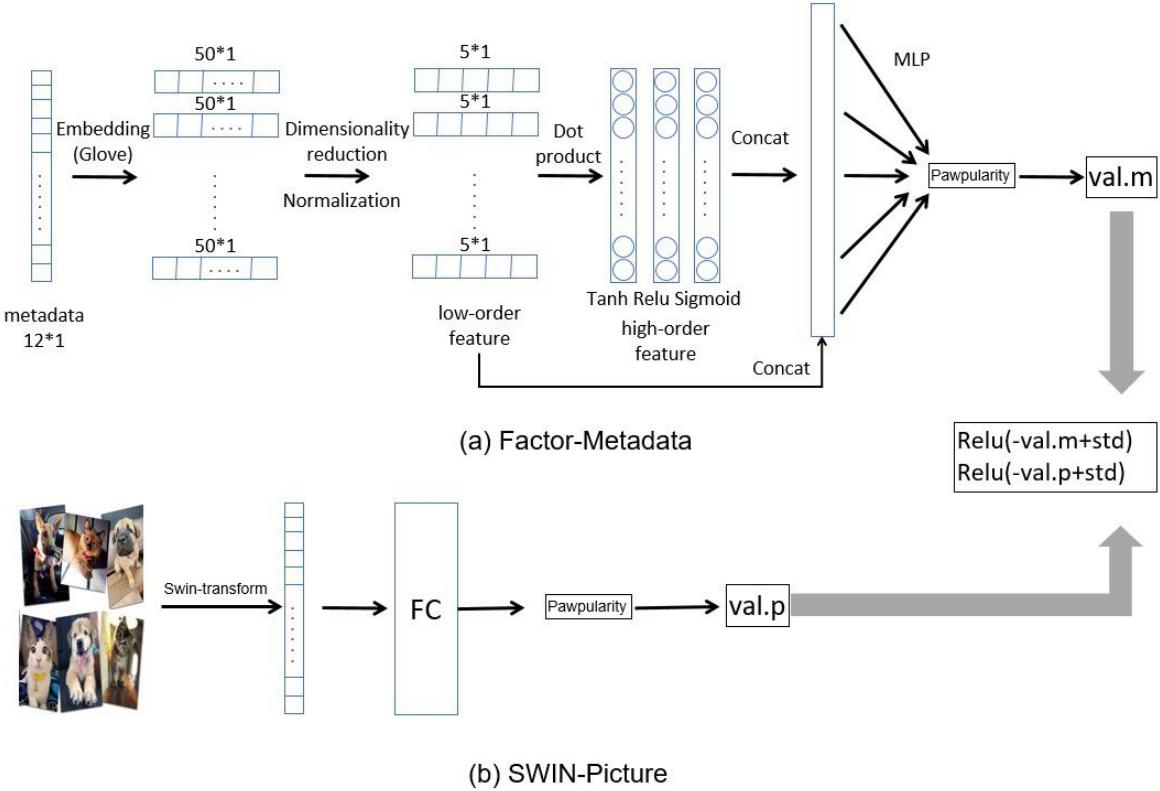


Fig. 2. The proposed PETS-SWINF architecture. (a) Metadata using Factorization-Machine (b) image using Swin-Transformer.

the high-order features and low-order features are concatenated, MLP is used for regression at last. Finally the RMSE loss of the validation set is obtained. Here, the loss functions of the validation set and the training set both use RMSE.

2.2. Images regression

Swin-Transformer [18] is adopted as the backbone network for pawpularity regression. The flowchart of the images model is as shown in Fig. 2 (b). We put images into Swin-Transformer, and then use MLP for regression. After our experiment, we found that the loss function of BCE is better than RMSE, so here we use BCE loss as the training loss and RMSE loss as the validation loss. The BCE loss formula is as follows,

$$\mathcal{L}_{BCE} = \frac{1}{N} \sum_{i=1}^N [y_i \cdot \log \tilde{y}_i + (1 - y_i) \cdot \log(1 - \tilde{y}_i)], \quad (2)$$

where N is the number of the data, and \tilde{y}_i and y_i is the model prediction and the label of the data.

Label of the data is normalized to 0 to 1, although the origin label of the data is integer 0 to 100. Pre-trained model of Swin-transformer is used before training. The configuration of Swin-Transformer will be introduced in the Section 4.

2.3. Parallelly fusion

Since two single models are used, we need to assign weights to each single model. We use the performance of the two models on the validation set to determine the weight distribution. The weight distribution adopts the following method,

$$w_{meta} = \frac{\text{Relu}(-val.m + std)}{\text{Relu}(-val.m + std) + \text{Relu}(-val.p + std)} \quad (3)$$

$$w_{pic} = \frac{\text{Relu}(-val.m + std)}{\text{Relu}(-val.m + std) + \text{Relu}(-val.p + std)}, \quad (4)$$

where $val.m$ and $val.p$ are the RMSE loss of the validation on the metadata and the image respectively. std selected as the standard is the deviation of the training data. The reason why std is used as a standard value is that if the mean of the label on training dataset is used as the prediction, then the RMSE will equal to std ,

$$std = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (label_i - u)^2}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (label_i - pred_i)^2},$$



Fig. 3. Similar images: the label of the duplicate images is different.

where N is the number of the training data, and u is the mean pawpularity of the training data. Therefore, if we use the mean value as a prediction, the RMSE loss of this model that does not require training is actually std when N is enough. So we take std as the worst model performance. If RMSE loss function on the validation set is smaller than std , the more weight is given. If the loss function is greater than std , we set the weight of this model to zero, because this model will bring negative effects.

3. Data analysis

There are 9912 images with metadata in the training set. The details of metadata will be introduced in [Appendix A](#). We find there are duplicate images in the training set, and the label of the duplicate image are different. We find the duplicate image by image perceptual hashing (perceptual hashes are "close" to one another if the images are similar). Because the number of the duplicate image is 54 as shown in [Fig. 3](#) (the total number of the images is 9912, a small proportion of the total image), we keep the duplicate images, in order to better make the model learn the noise of the data. Our experiments show that keeping duplicate images performs better on the test set than deleting them ³.

The statistical characteristics of the images are analyzed. We analyzed image height and width distri-

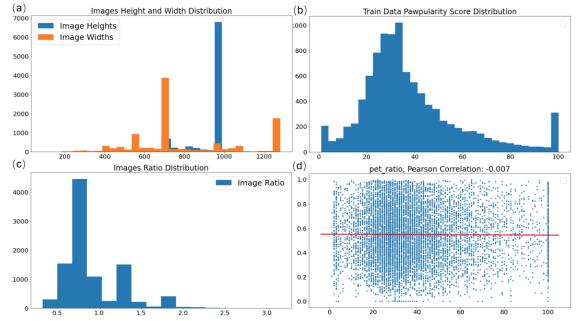


Fig. 4. The statistical characteristic of the data by Exploratory Data Analysis.

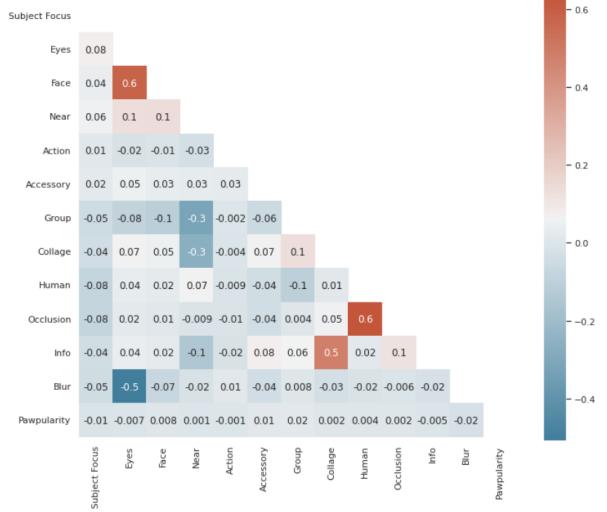


Fig. 5. The correlation between the meta 12 features and the pawpularity.

bution, ratio distribution ($width/height$), and pawpularity distribution on the train data. [Fig. 4](#) (a) and (c) show the size distribution of the images, we can find that most of the images are taken by mobile phones. [Fig. 4](#) (b) shows that the distribution of the pawpularity is similar to the gauss distribution, and the amount of the data pawpularity at both ends is particularly large due to the upper and lower limit. Experiments show that keeping extreme images (pawpularity 100 or 0) is better than deleting them. [Fig. 4](#) (d) shows there is a few correlations between the image ratio and pawpularity.

There are 12 features in the metadata detailed in [Appendix A](#). We use Correlation Matrix between the meta features and the pawpularity as shown in [Fig. 5](#). We can find that there are a few relations between all the meta-features and particularity. Although the linear correlation between metadata and pawpularity is low, there may exist a nonlinear relationship. Therefore, it is important to design nonlinearities in metadata networks. This is the reason for the design of high-order features.

The pawpularity label is derived from each pet pro-

³Data analysis is inspired by <https://www.kaggle.com/markwijkhuizen/petfinder-edayolov5-obj-detection-tfrecords>

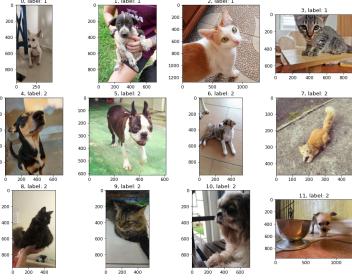


Fig. 6. Lowest pawpularity.

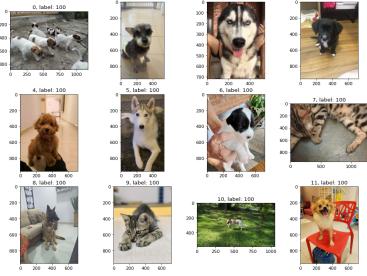


Fig. 7. Largest pawpularity.

file's page view statistics at the listing pages, using an algorithm that normalizes the traffic data across different pages, platforms (web & mobile) and various metrics. We visualize the extreme cases as shown in Fig. 6 and Fig. 7. We can find that there is a big difference between the pawpularity and our cognitive loveliness (the image 2 in Fig. 6 should have more pawpularity than its label and the image 8 in Fig. 7 is too average to deserve a full score of 100). The pawpularity score is related to the time the animal started to be shown in web, because the derivation of the pawpularity is strongly related to the traffic.

There are only two kinds of animals (dog and cat) in the dataset. It is reasonable that dogs and cats are judged differently. There is no classified information in the dataset, so we use the yolov5 (yolov5x6) in object detection to classify the images. Fig. 8 shows the results of the yolov5 only about cats and dogs and Fig. 9 shows the unknown results of the yolov5. Fig. 10 shows that the boxplot of classifications of the image and the number of the animals in one image both are different.

4. Results and discussion

To conduct our experiments, the proposed PETS-SWINF architecture achieved RMSE 17.71876 with data augmentations on the test dataset, and win the gold medal (currently ranked 12/3393). As shown in Table 1, we compare our results without data augmentations and without metadata.

We use RandomErasing, Rotate, Brightness, Flip, Contrast, Saturation as the data augmentation con-

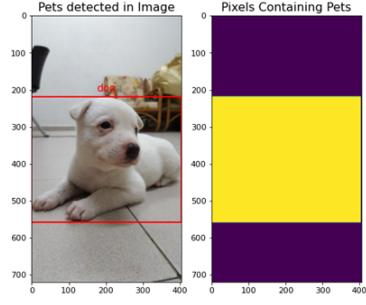


Fig. 8. The result about cats and dogs of the yolov5.



Fig. 9. The result unknown of the yolov5.

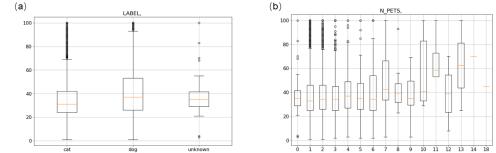


Fig. 10. The correlation between the classification (dogs and cats) and the pawpularity (a), the correlation between the number of animals (dogs and cats) in one image and the pawpularity (b).

Table 1

Results obtained from PETS-SWINF, PETS-SWINF without data augmentation, and PETS-SWINF without metadata. PETS-SWINF without data augmentation has metadata regression models. PETS-SWINF without metadata has data augmentation. PETS-SWINF has data augmentation and metadata regression models.

	Val accuracy	Test accuracy
PETS-SWINF without data augmentation	17.68121	17.88243
PETS-SWINF without metadata	17.48691	17.76449
PETS-SWINF	17.42164	17.71876

figuration. Batch size is 40; KFLOD is 10; Learning rate is 2e-5. Swin_large_patch4_window7_224 is adopted as the backbone network for the image regression. TTA (Test-Time Data Augmentation) as the training data augmentation configuration is used in the inference period.

It can be found from [Table 1](#) that data augmentations and the rational use of metadata improve the accuracy of the validation set and the test set. This is because there are not enough data in the training set, so the data augmentations can have a good effect. In addition, these augmentation techniques have a certain intersection with the nature of the pawpularity prediction problem. Although it can be seen from [Fig. 5](#) that independent metadata have little effect on pawpularity, it cannot be ruled out that some nonlinear combinations of metadata are independent to pawpularity. Therefore, The metadata processing of PETS-SWINF establishes the correlation between nonlinear features (low-order features and high-order features) through the neural network and the cuteness. The model uses the loss of the validation set to perform the weighting fusion, which shows that the weighting method of model fusion is useful from the result of PETS-SWINF without metadata and PETS-SWINF.

5. Conclusion

Millions of stray animals around the world suffer in the streets or are euthanized in shelters every day. If more stray animals can be adopted by caring people as their own pets, it will greatly reduce the number of stray animals. In order to better adopt stray animals, it is necessary to score the pawpularity of stray animals, but evaluating the pawpularity of animals is a very labor-intensive thing. In this study, we proposed a PETS-SWINF architecture, for prediction of the pawpularity from pets images with metadata. The proposed method win the gold medal in Kaggle competition called 2021 PetFinder.my (currently ranked 18/3537).

The proposed method is a regression model, which can combines images with metadata. The way of assigning weight can adaptively use images or metadata. In addition, the metadata model can fuse low-

order features and high-order features. The proposed PETS-SWINF model is available publicly for open access at <https://github.com/yizheng-wang/PETS-SWINF>.

The proposed method can be widely used in image regression tasks with metadata, such as CTR (click-through rate prediction). As more and more stray animals are being labeled all around the world, larger datasets are being generated. We will continue to further modify the architecture of the proposed PETS-SWINF and incorporate new available datasets. New versions of the PETS-SWINF will be released upon development through the aforementioned link.

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Appendix A. Metadata

- Focus - Pet stands out against uncluttered background, not too close / far.
- Eyes - Both eyes are facing front or near-front, with at least 1 eye / pupil decently clear.
- Face - Decently clear face, facing front or near-front. \item Near - Single pet taking up significant portion of photo (roughly over 50% of photo width or height).
- Action - Pet in the middle of an action (e.g., jumping).
- Accessory - Accompanying physical or digital accessory / prop (i.e. toy, digital sticker), excluding collar and leash.
- Group - More than 1 pet in the photo.
- Collage - Digitally-retouched photo (i.e. with digital photo frame, combination of multiple photos).

- Human - Human in the photo. \item Occlusion - Specific undesirable objects blocking part of the pet (i.e. human, cage or fence). Note that not all blocking objects are considered occlusion.
- Info - Custom-added text or labels (i.e. pet name, description).
- Blur - Noticeably out of focus or noisy, especially for the pet's eyes and face. For Blur entries, "Eyes" column is always set to 0.

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