Exploring Pawpularity of Pet Profiles

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Project Description

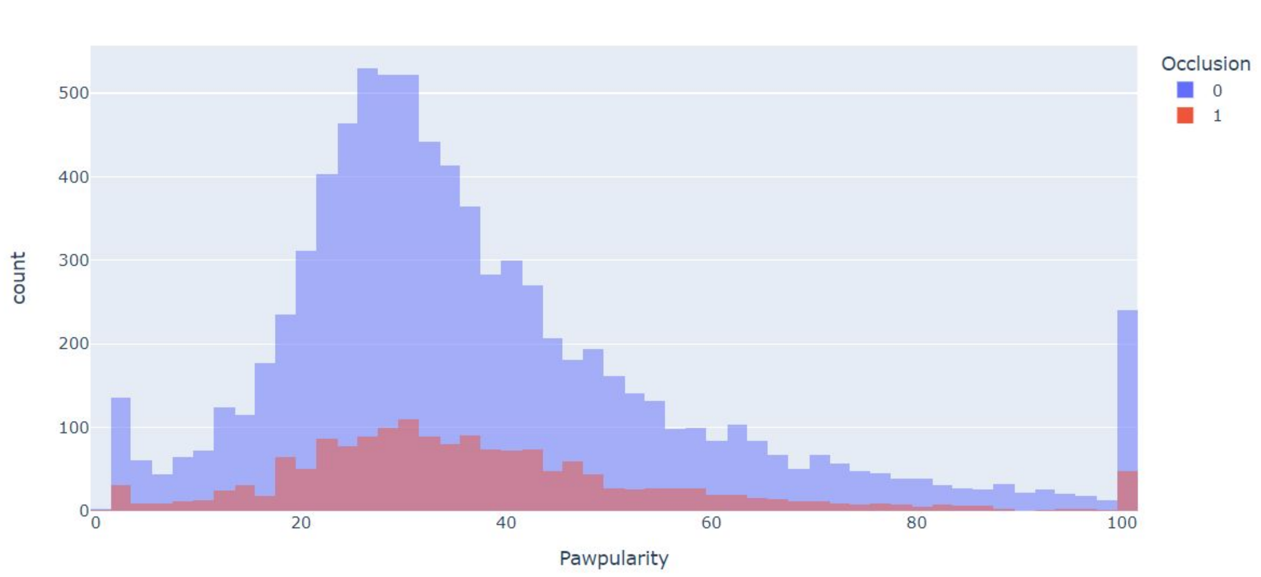
PetFinder.my is a platform in Malaysia that has a database of 180,000 pet profiles for pets up for adoption.
The webpage automatically calculates a "Pawpularity" score based on the web page activity for each profile. To better the lives of pets and ensure they find their forever home, we hope to identify how to make a pet's profile more pawpular.
The goal of this project, based upon a Kaggle competition, is to accurately predict the pawpularity of the pets based solely upon their profiles, and identify what makes them so pawpular. To achieve this, we will use multiple models to analyze the provided images and metadata to construct a model to predict pawpularity scores. Our performance metric will be the Root Mean Square Error (RMSE), as used in the competition.

Aim

1. Identify what features make a pet "pawpular"
2. Accurately predict the Pawpularity score of a pet profile

The Data and Exploration

- We information on 9,912 Pet Profiles
  - This includes 9,912 Images
  - Metadata on Subject Focus, Eyes, Face, Near, Action, Accessory, Group, Collage, Info, Human, Occlusion, Blur, Pawpularity Score
  - These would be split 80-20% into Test and Train
- To visualize it we plotted the correlation matrix of features and distribution of pawpularity. Pretty uniform spread, and no correlations :(



Subject Focus	1.00	0.08	0.04	0.06	0.01	0.02	-0.05	-0.04	-0.08	-0.08	-0.04	-0.05	-0.01
Eyes	0.08	1.00	0.58	0.13	-0.02	0.05	-0.08	0.07	0.04	0.02	0.04	-0.51	-0.01
Face	0.04	0.58	1.00	0.14	-0.01	0.03	-0.11	0.05	0.02	0.01	0.02	-0.07	0.01
Near	0.06	0.13	0.14	1.00	-0.03	0.03	-0.32	-0.26	0.07	-0.01	-0.15	-0.02	0.00
Action	0.01	-0.02	-0.01	-0.03	1.00	0.03	-0.00	-0.00	-0.01	-0.01	-0.02	0.01	-0.00
Accessory	0.02	0.05	0.03	0.03	0.03	1.00	-0.06	0.07	-0.04	-0.04	0.08	-0.04	0.01
Group	-0.05	-0.08	-0.11	-0.32	-0.00	-0.06	1.00	0.13	-0.10	0.00	0.06	0.01	0.02
Collage	-0.04	0.07	0.05	-0.26	-0.00	0.07	0.13	1.00	0.01	0.05	0.48	-0.03	0.00
Human	-0.08	0.04	0.02	0.07	-0.01	-0.04	-0.10	0.01	1.00	0.63	0.02	-0.02	0.00
Occlusion	-0.08	0.02	0.01	-0.01	-0.01	-0.04	0.00	0.05	0.63	1.00	0.12	-0.01	0.00
Info	-0.04	0.04	0.02	-0.15	-0.02	0.08	0.06	0.48	0.02	0.12	1.00	-0.02	-0.00
Blur	-0.05	-0.51	-0.07	-0.02	0.01	-0.04	0.01	-0.03	-0.02	-0.01	-0.02	1.00	-0.02
Pawpularity	-0.01	-0.01	0.01	0.00	-0.00	0.01	0.02	0.00	0.00	0.00	-0.00	-0.02	1.00

Methods

We utilized 3 different approaches to tackle this problem:

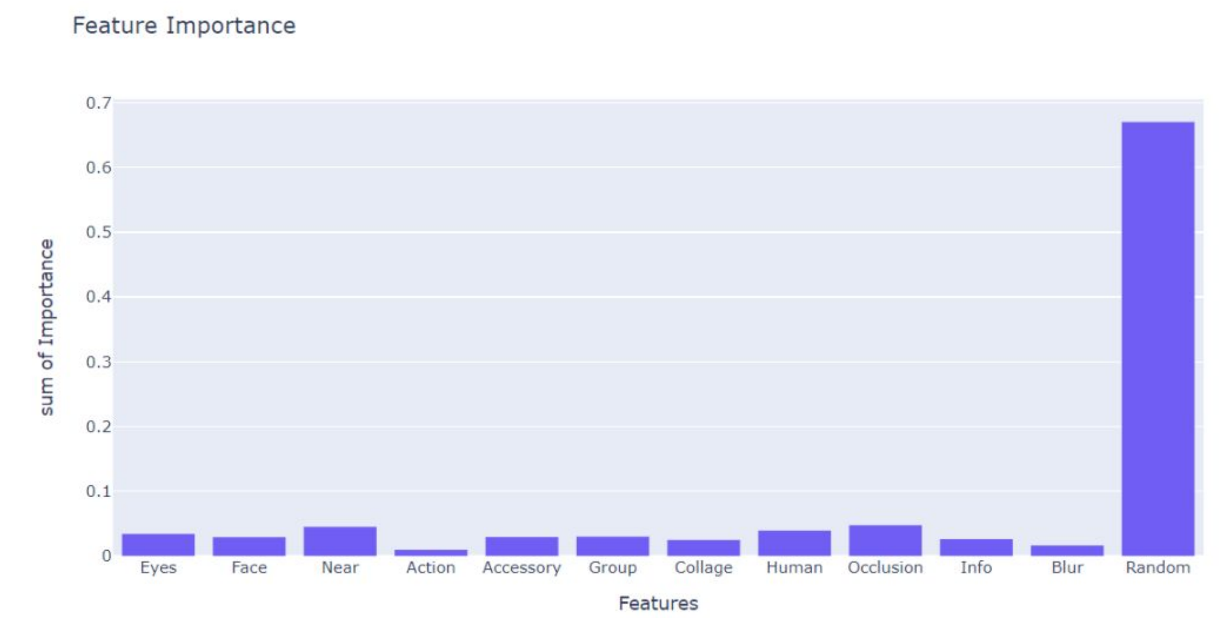
- A Random Forest Regressor
  - This was chosen to explore the metadata to gather the feature importance in reference to popularity
  - In addition this was isolated from the picture data to provide a baseline
- A Convolutional Neural Network
  - Chosen for its practicality in analyzing large samples of images, we built this network as a regression model.
  - Feeding images, reshaped to (64,64), into the model, we sought trained using RMSE as our metric, and trained against Pawpularity. Our goal for success was RMSE < 21

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_3 (Conv2D)            (None, 60, 60, 30)        2280
_________________________________________________________________
batch_normalization_4 (Batch (None, 60, 60, 30)        120
_________________________________________________________________
dropout_2 (Dropout)          (None, 60, 60, 30)        0
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 30, 30, 30)        0
_________________________________________________________________
batch_normalization_5 (Batch (None, 30, 30, 30)        120
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 26, 26, 25)        18775
_________________________________________________________________
dropout_3 (Dropout)          (None, 26, 26, 25)        0
_________________________________________________________________
batch_normalization_6 (Batch (None, 26, 26, 25)        100
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 13, 13, 25)        0
_________________________________________________________________
batch_normalization_7 (Batch (None, 13, 13, 25)        100
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 11, 11, 32)        7232
_________________________________________________________________
flatten_1 (Flatten)          (None, 3872)              0
_________________________________________________________________
dense_3 (Dense)              (None, 64)                247872
_________________________________________________________________
dense_4 (Dense)              (None, 32)                2080
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 33
=================================================================
Total params: 278,712
Trainable params: 278,492
Non-trainable params: 220
```

Fearing there weren't adequate features we also utilized a transfer learning algorithm

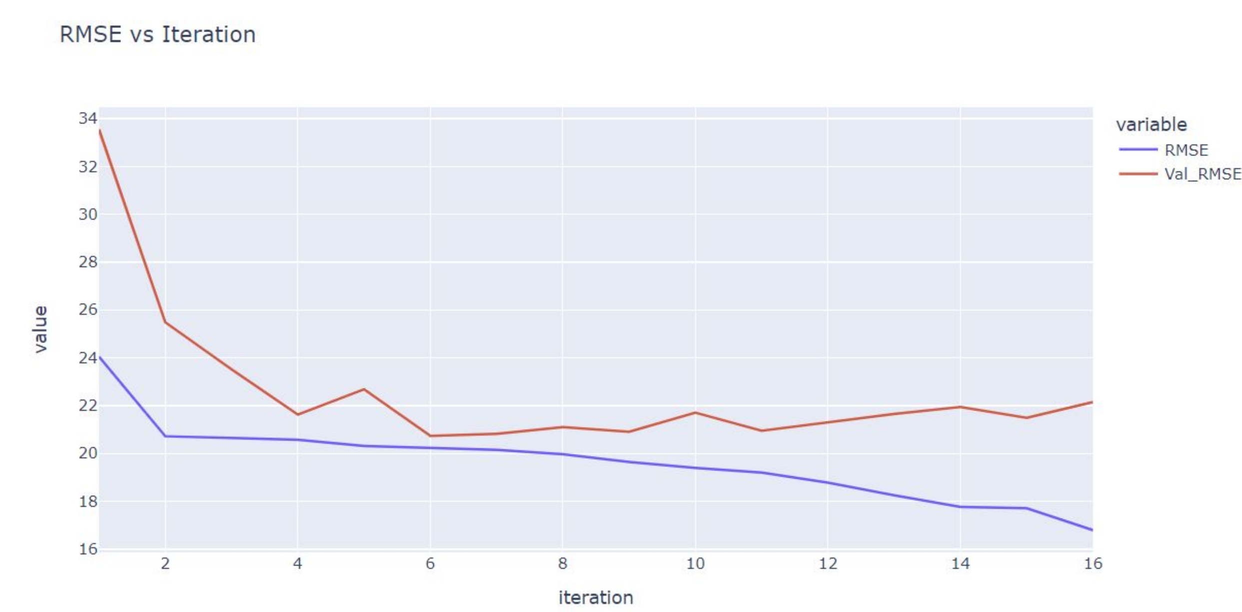
- A pretrained model, VGG16 from Keras, was utilized to extract additional features from our images, such as information on dog/cat breed. This greatly expanded our original data set
- We fed our images through this model, then transferred the features to a Random Forest Regressor.
- With additional features, we used this random forest to calculate a new RMSE score when training the model against Pawpularity

Results of RF Regression



- Unfortunately, no feature was important, except for the random integers.

Results of CNN

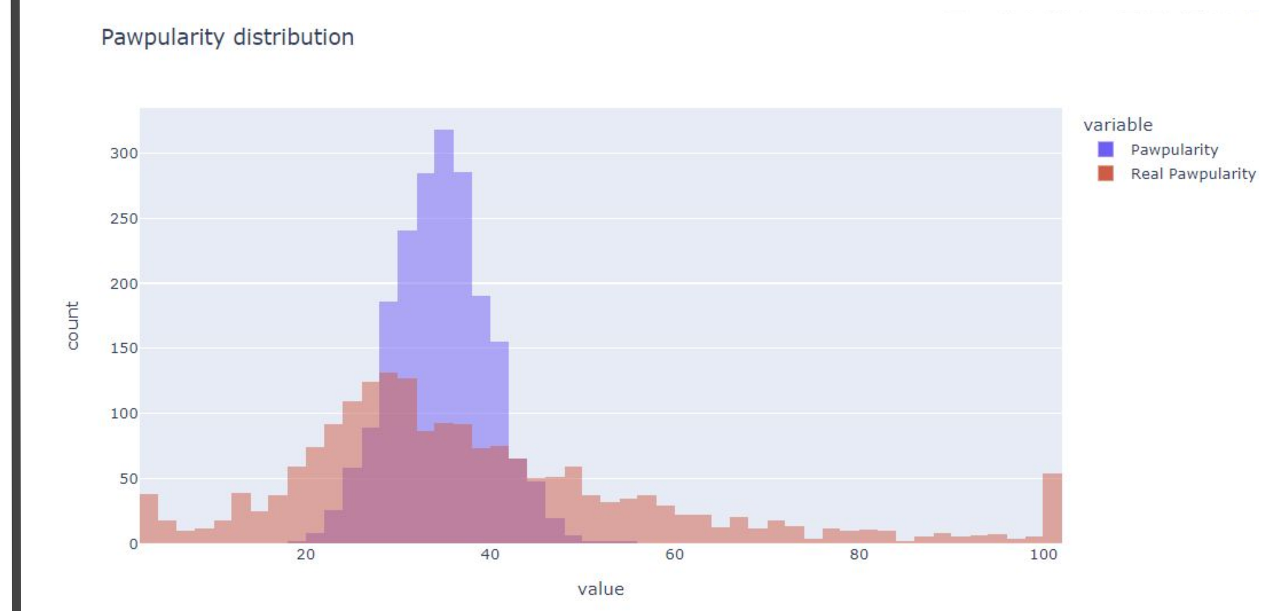


- Best RMSE achieved was 20.643
  - Near the average score, but model doesn't improve
  - Oscillates around 20.5-21, Suggests not much correlation could be pulled out

Results of Transfer Learning

- Best RMSE achieved across all tests was 20.29
  - There is a little improvement, but still leaves much to desired

Results Continued



- Here we can see our model plays it safe by predicting pawpularity, uniformly around the average value.
- This shows that from the initial data there still wasn't a strong trend determining pawpularity
- This indicates that there is likely other mechanisms behind a pet's cuteness/pawpularity that can be further explored.

Conclusions

- Neither an animals breed, nor the explored features of the profile determines a pets Pawpularity.
- It is likely that other features in the pet profile determine how popular the page is
- Moving forward there are many improvements that could made to both the model and the process
  - An option is to use a stronger pretrained model such as Swin, to extract more features from the pet's image
  - Additionally more data from the pet's characteristics could be explored such as Age, Temperament, Health, Size, etc. that are things considered when adding a new friend to the home
  - Finally features of the site itself, such as upload time, history of a page, duration the page has existed, may be factors determining traffic.
- But in the end a pet's cuteness is subjective, and could be less of a science than thought. In reality each of the pets up are equally deserving of adoption and finding their forever homes.

References

https://www.kaggle.com/competitions/petfinder-pawpularity-score/overview

Dr. Hughes

https://machinelearningmastery.com/how-to-use-transfer-learning-when-developing-convolutional-neural-network-models/

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