Warning: Do not run notebook, certain cells take upwards of 30 minutes to an hour to run!!!

Petfinder Pawpularity Prediction Using Neural Networks

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Contents

Overview

> Petfinder.my (https://www.petfinder.my/) is Malaysia's leading animal welfare platform, featuring over 200,000 animals with more than 56,000 happily adopted. This project analyzes photos of adoptable pets from Malaysian animal shelters found on Petfinder and designs a Deep Learning model to predict the "Pawpularity" of pet photos.

Business Understanding

> They say a picture is worth a thousand words. A picture can also save a life. Hundreds of millions of stray cats and dogs suffer on the streets, live miserably in crowded shelters, or are euthanized around the world. Companion animals with attractive and high quality photos are more likely to be adopted and more likely to be adopted faster [source (https://www.tandfonline.com/doi/full/10.1080/10888705.2014.982796)](https://www.tandfonline.com/doi/full/10.1080/10888705.2014.982796). We want to answer the question: what makes a good picture? After analyzing raw images and metadata to predict the “Pawpularity” of pet photos, we train and test our model on PetFinder.my's thousands of pet profiles to come up with the best recommendations on photo composition. We hope our model will help stray cats and dogs find their "furever" home faster.

Data Understanding

> The data comes from thousands of pet profiles on [Petfinder.my (https://www.petfinder.my/)](https://www.petfinder.my/). The `Pawpularity` score is derived from each pet profile'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. Duplicate clicks, crawler bot accesses and sponsored profiles are excluded from the analysis. All the feature metadata is explained [here (https://github.com/stevenaddison/Project-4/blob/main/data/metadata.md)](https://github.com/stevenaddison/Project-4/blob/main/data/metadata.md).

Imports

> First, we start with importing the relevant libraries to load and clean our dataset.

In [1]:
```
#pip install opencv-python
#pip install scikit-image
```

In [2]:
```
import numpy as np
import pandas as pd
import cv2
import tensorflow as tf
import keras

from skimage.transform import resize
from skimage import color, io

from scipy import ndimage

from sklearn.model_selection import train_test_split
from sklearn.dummy import DummyRegressor
from sklearn.metrics import mean_squared_error as mse

from keras.models import Sequential
from keras.layers import Dense, Flatten, Conv2D, MaxPooling2D, Dropout
from keras.losses import MeanSquaredError
from keras.metrics import RootMeanSquaredError

import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
```

```
/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/skimage/io/manage_plu
gins.py:23: UserWarning: Your installed pillow version is < 8.1.2. Several secu
rity issues (CVE-2021-27921, CVE-2021-25290, CVE-2021-25291, CVE-2021-25293, an
d more) have been fixed in pillow 8.1.2 or higher. We recommend to upgrade this
library.
  from .collection import imread_collection_wrapper
```

Data Preparation & Analysis

In [3]:
```
# Open .csv file as pandas dataframe
df = pd.read_csv("data/train.csv")
```

In [4]:
```
# Initial look at dataframe
df.head()
```

Out[4]:

	Id	Subject Focus	Eyes	Face	Near	Action	Accessory	Group	Coll
0	0007de18844b0dbbb5e1f607da0606e0	0	1	1	1	0	0	1	
1	0009c66b9439883ba2750fb825e1d7db	0	1	1	0	0	0	0	
2	0013fd999caf9a3efe1352ca1b0d937e	0	1	1	1	0	0	0	
3	0018df346ac9c1d8413cfcc888ca8246	0	1	1	1	0	0	0	
4	001dc955e10590d3ca4673f034feeef2	0	0	0	1	0	0	1	

In [5]:
```
# Count of non-null values, datatypes, and total entries
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9912 entries, 0 to 9911
Data columns (total 14 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   Id             9912 non-null   object
 1   Subject Focus  9912 non-null   int64 
 2   Eyes           9912 non-null   int64 
 3   Face           9912 non-null   int64 
 4   Near           9912 non-null   int64 
 5   Action         9912 non-null   int64 
 6   Accessory      9912 non-null   int64 
 7   Group          9912 non-null   int64 
 8   Collage        9912 non-null   int64 
 9   Human          9912 non-null   int64 
 10  Occlusion      9912 non-null   int64 
 11  Info           9912 non-null   int64 
 12  Blur           9912 non-null   int64 
 13  Pawpularity    9912 non-null   int64 
dtypes: int64(13), object(1)
memory usage: 1.1+ MB
```

In [6]:
```
# Check descriptive statistics
df.describe()
```

Out[6]:

	Subject Focus	Eyes	Face	Near	Action	Accessory	Group
count	9912.000000	9912.000000	9912.000000	9912.000000	9912.000000	9912.000000	9912.000000
mean	0.027643	0.772599	0.903955	0.861582	0.009988	0.067797	0.129338
std	0.163957	0.419175	0.294668	0.345356	0.099444	0.251409	0.335591
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	1.000000	1.000000	1.000000	0.000000	0.000000	0.000000
50%	0.000000	1.000000	1.000000	1.000000	0.000000	0.000000	0.000000
75%	0.000000	1.000000	1.000000	1.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

In [7]:
```python
# Check value counts
for c in df.columns:
    print ("---- %s ----" % c)
    print (df[c].value_counts())
    print("\n")
```

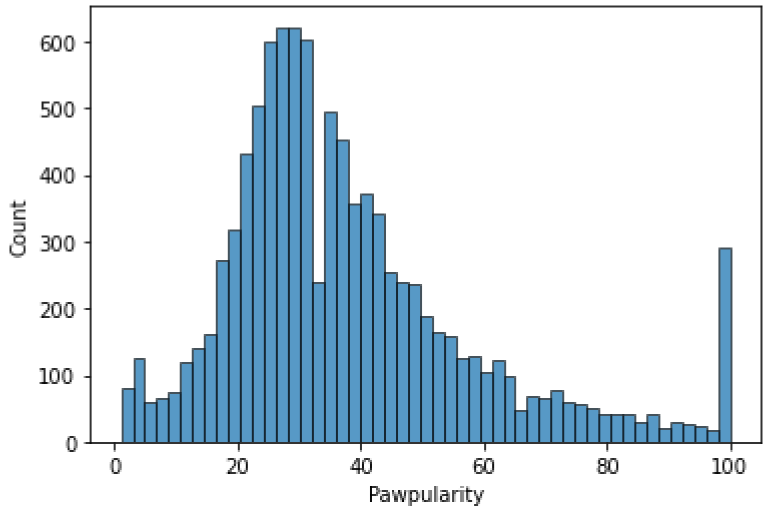
```
---- Id ----
a9894bf4223185f48188a545044aeefa    1
c97498a8f67676fed254ae35e735a312    1
d20cf059a9e892dcb8bb991bf5acf010    1
b6004a1d03498ef6ef362685e38535e2    1
2aee7c914c13f432e20c842ce71dbfd9    1
                                   ..
a450cd16e284e1fc9affba674a63c154    1
4a4b92b7387e75223b2fd1e502e71ce3    1
5dadbfa60882b172cc2f0710aaefb9f1    1
87abac899ef38e21df16edab73e05307    1
efc51b5700c80e739d81f83bd21ef735    1
Name: Id, Length: 9912, dtype: int64


---- Subject Focus ----
0    9638
1     274
Name: Subject Focus, dtype: int64


---- Eyes ----
1    7658
0    2254
Name: Eyes, dtype: int64


---- Face ----
1    8960
0     952
Name: Face, dtype: int64


---- Near ----
1    8540
0    1372
Name: Near, dtype: int64


---- Action ----
0    9813
1      99
Name: Action, dtype: int64


---- Accessory ----
0    9240
1     672
Name: Accessory, dtype: int64
```

```
---- Group ----
0    8630
1    1282
Name: Group, dtype: int64


---- Collage ----
0    9420
1     492
Name: Collage, dtype: int64


---- Human ----
0    8264
1    1648
Name: Human, dtype: int64


---- Occlusion ----
0    8207
1    1705
Name: Occlusion, dtype: int64


---- Info ----
0    9305
1     607
Name: Info, dtype: int64


---- Blur ----
0    9214
1     698
Name: Blur, dtype: int64


---- Pawpularity ----
28    318
30    318
26    316
31    312
29    304
     ...
98     10
97      8
90      7
1       4
99      4
Name: Pawpularity, Length: 100, dtype: int64
```

There are 9912 images and 12 features: `Subject Focus`, `Eyes`, `Face`, `Near`, `Action`, `Accessory`, `Group`, `Collage`, `Human`, `Occlusion`, `Info`, and

`Blur` . The target variable is `Pawpularity` and ranges from 1-100. There are no null values and all features have a value of 0 (no) or 1 (yes).

In [8]:
```
sns.histplot(df['Pawpularity']);
```

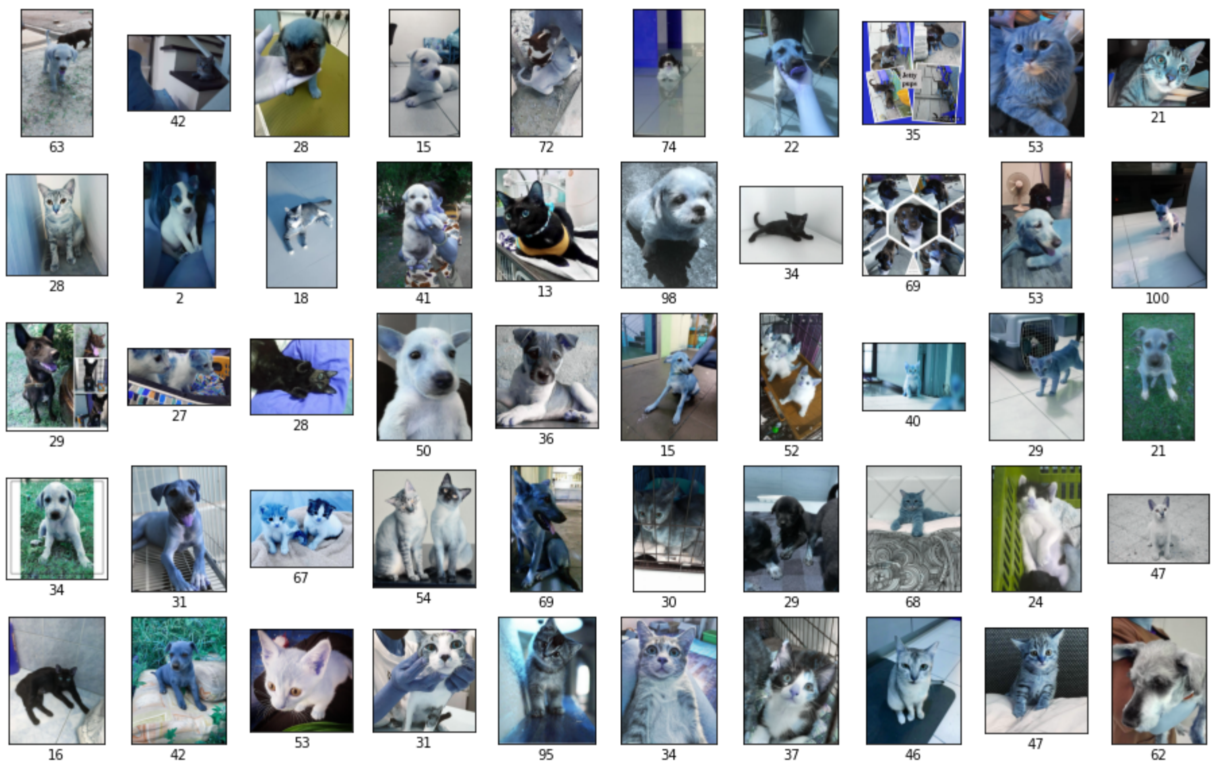


Here we take at a look at the distribution of the target `Pawpularity` and see a spike at 100.

In [9]:
```
# Download images to notebook
images = []
count = 0
for index in range(len(df)):
    Id = df.loc[index, 'Id']
    path = 'data/train/'+str(Id)+'.jpg'
    img_array = cv2.imread(path)
    img_array = resize(img_array, (128, 128), anti_aliasing=True)
    images.append(img_array)
    count += 1
    progress = (count/len(df))*100
    print('progress =', round(progress,2), '%', end='\r')
```

```
progress = 100.0 %12.08 %
```

In [10]:
```
# Plot first 50 images
def image_read(path):
    return cv2.imread(path)

df['path'] = df.apply(lambda x : 'data/train/' + x['Id'] + ".jpg", axis=1)
fig, ax = plt.subplots(5,10,figsize=(16, 10))
for i, (path, score) in enumerate(df[['path', 'Pawpularity']][:50].values.tolist(
    row, col = i // 10, i % 10
    axis = ax[row][col]
    axis.imshow(image_read(path))
    axis.set_xticks([])
    axis.set_yticks([])
    axis.set_xlabel(score)
plt.show()
```



We see a variety of cat and dog photos and their `Pawpularity` score. Something we notice is that the photos lean blue but do not know why and cannot find more information on this.

In [11]:
```
# Transforming images list to numpy array for modeling and assigning it to X and
X = np.array(images)
y = df['Pawpularity']

# Checking shape of X
X.shape
```

Out[11]: (9912, 128, 128, 3)

In [12]:
```
# Do a train-test-split using a random state of 42 for reproducibility
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42)
```

Modeling

> We start by creating functions for model building and evaluation to streamline our process.

In [13]:
```
# Function for model building
def model_compfit(model, X_train, y_train, n_epochs):
    """Function to compile our models using our chosen optimizer, loss,
    and evaluation metrics. The function then fits the model on our train
    data and n number epochs, finally printing out a model summary."""

    # compile model with adam optimizer and mean squared error metric
    model.compile(optimizer='adam',
              loss=MeanSquaredError(),
              metrics=[RootMeanSquaredError()])
    # fit model on train sets with n number epochs
    model.fit(X_train, y_train, epochs=n_epochs)

    #print model summary
    model.summary()
```

In [14]:
```
# Function for model evaluation
def model_eval(model, X_train, y_train, X_test, y_test, name):
    """Function to evaluate our model on the training and test
    data, then printing out those metrics, and visualizing the
    predictions on the test data."""

    # calculate training data metrics
    train_eval = model.evaluate(X_train, y_train)

    # calculate test data metrics
    test_eval = model.evaluate(X_test, y_test)

    # print metrics
    print(f"""
    {name} Training Metrics:
    Loss: {round(train_eval[0] , 3)}
    RMSE: {round(train_eval[1] , 3)}
    ------
    {name} Test Metrics:
    Loss: {round(test_eval[0] , 3)}
    RMSE: {round(test_eval[1] , 3)}
    """)

    # visualize predictions
    ypred = model.predict(X_test)
    x_ax = range(len(ypred))
    plt.figure(figsize=(20,10))
    plt.scatter(x_ax, y_test, s=15, color="blue", label="original")
    plt.plot(x_ax, ypred, lw=1, color="red", label="predicted")
    plt.legend()
    plt.show()
```

Baseline Dummy Regressor

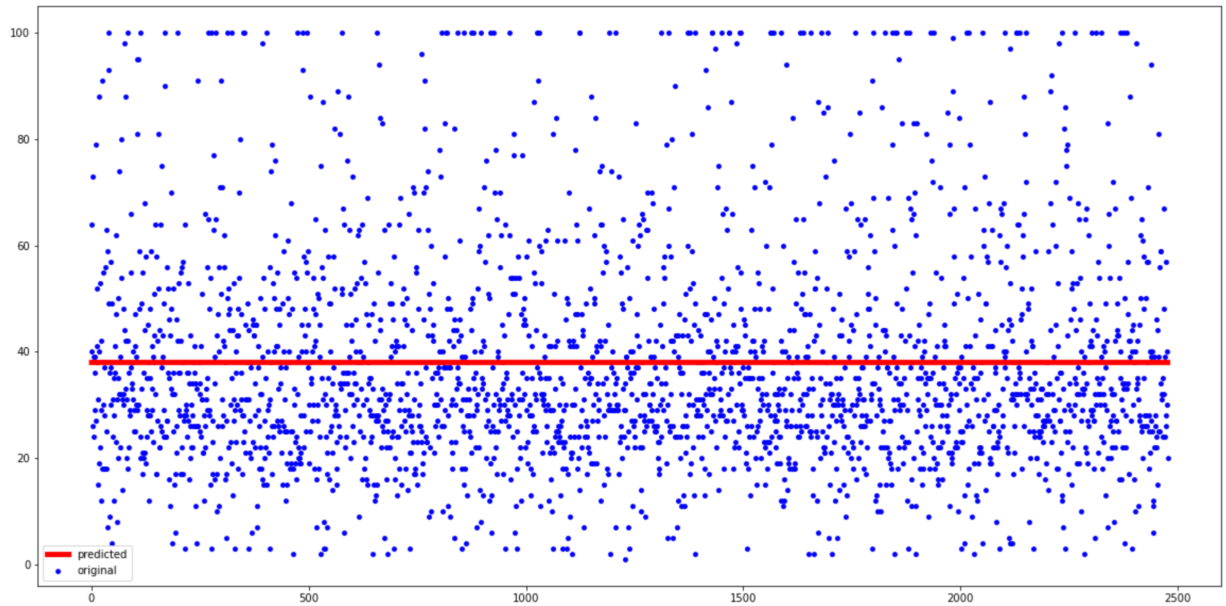
> We start off with a Baseline Dummy Regressor to compare our models to and try to improve upon.

In [15]:
```
baseline = DummyRegressor(strategy="mean")
baseline.fit (X_train,y_train)
y_hat_test = baseline.predict(X_test)
baseline_rmse = mse(y_test, y_hat_test, squared=False)
```

In [16]:
```
baseline_rmse
```

Out[16]:
```
21.074920522735773
```

In [17]:
```
ypred = baseline.predict(X_test)
x_ax = range(len(ypred))
plt.figure(figsize=(20,10))
plt.scatter(x_ax, y_test, s=15, color="blue", label="original")
plt.plot(x_ax, ypred, lw=5, color="red", label="predicted")
plt.legend()
plt.show()
```



First Basic Model and Image Augmentation

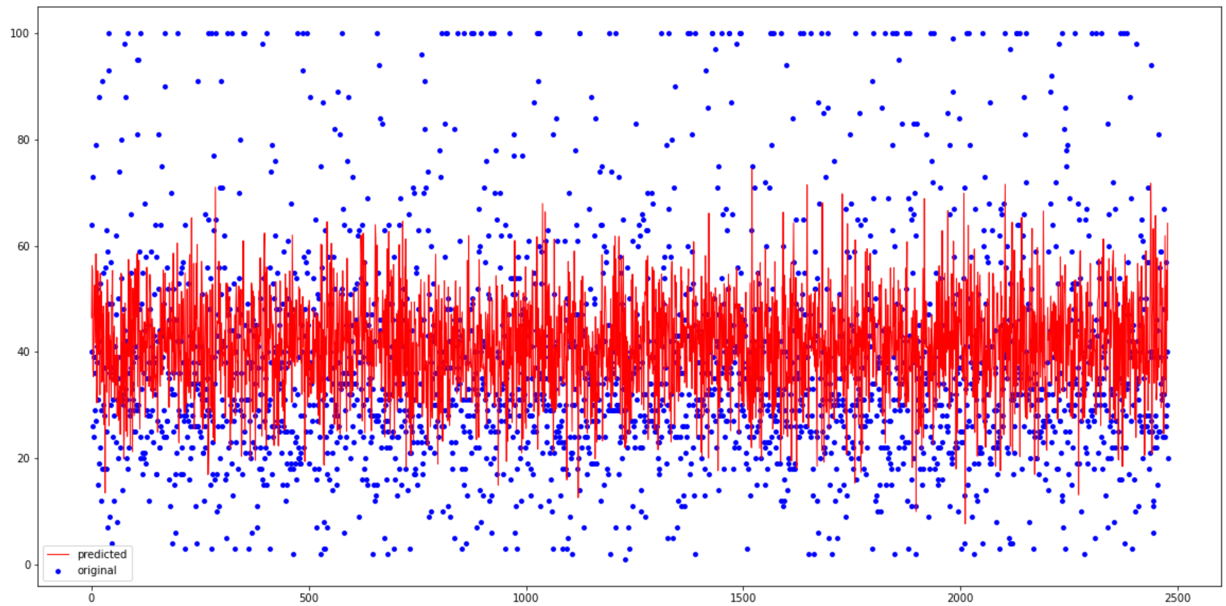
Our first basic model is an Artificial Neural Network with one layer.

In [18]:
```
basicann = Sequential([
            Flatten(),
            Dense(1, activation='relu')
          ])

model_compfit(basicann, X_train, y_train, 10)
```

```
Epoch 1/10
233/233 [==============================] - 2s 7ms/step - loss: 498.5932 - root_
mean_squared_error: 22.3292
Epoch 2/10
233/233 [==============================] - 1s 5ms/step - loss: 499.8664 - root_
mean_squared_error: 22.3577
Epoch 3/10
233/233 [==============================] - 1s 5ms/step - loss: 479.0622 - root_
mean_squared_error: 21.8875
Epoch 4/10
233/233 [==============================] - 1s 5ms/step - loss: 488.3990 - root_
mean_squared_error: 22.0998
Epoch 5/10
233/233 [==============================] - 1s 4ms/step - loss: 474.0719 - root_
mean_squared_error: 21.7732
Epoch 6/10
233/233 [==============================] - 1s 5ms/step - loss: 471.8141 - root_
mean_squared_error: 21.7213
Epoch 7/10
233/233 [==============================] - 1s 5ms/step - loss: 471.9232 - root_
mean_squared_error: 21.7238
Epoch 8/10
233/233 [==============================] - 2s 10ms/step - loss: 465.8413 - root
_mean_squared_error: 21.5834
Epoch 9/10
233/233 [==============================] - 2s 8ms/step - loss: 458.4019 - root_
mean_squared_error: 21.4103
Epoch 10/10
233/233 [==============================] - 1s 5ms/step - loss: 470.1948 - root_
mean_squared_error: 21.6840
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten (Flatten)            (None, 49152)             0
_________________________________________________________________
dense (Dense)                (None, 1)                 49153
=================================================================
Total params: 49,153
Trainable params: 49,153
Non-trainable params: 0
_________________________________________________________________
```

In [19]:
```
model_eval(basicann, X_train, y_train, X_test, y_test, 'Basic ANN')
```

```
233/233 [==============================] - 2s 10ms/step - loss: 453.5609 - root
_mean_squared_error: 21.2970
78/78 [==============================] - 0s 5ms/step - loss: 528.6611 - root_me
an_squared_error: 22.9926

    Basic ANN Training Metrics:
    Loss: 453.561
    RMSE: 21.297
    ------
    Basic ANN Test Metrics:
    Loss: 528.661
    RMSE: 22.993
```

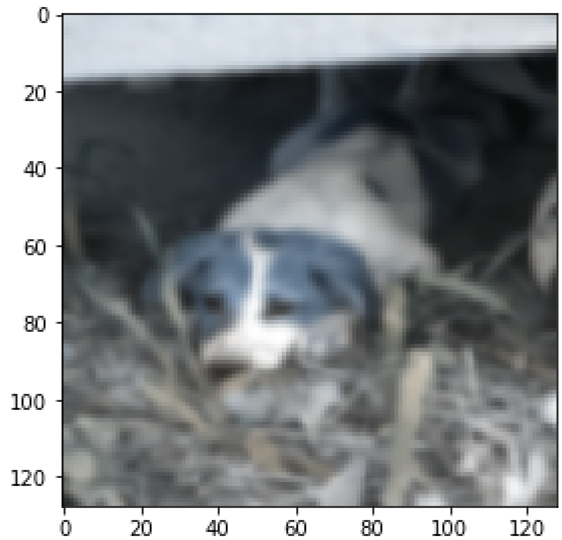


We do some image augmentation by blurring the photos to see how that affects our RMSE.

In [20]:
```
X_train_blur = []

for image in X_train:
    image = ndimage.gaussian_filter(image, sigma= 1)
    X_train_blur.append(image)

X_train_blur = np.array(X_train_blur)
```

In [21]:
```
io.imshow(X_train_blur[0])
```

Out[21]: <matplotlib.image.AxesImage at 0x7fabae4590d0>

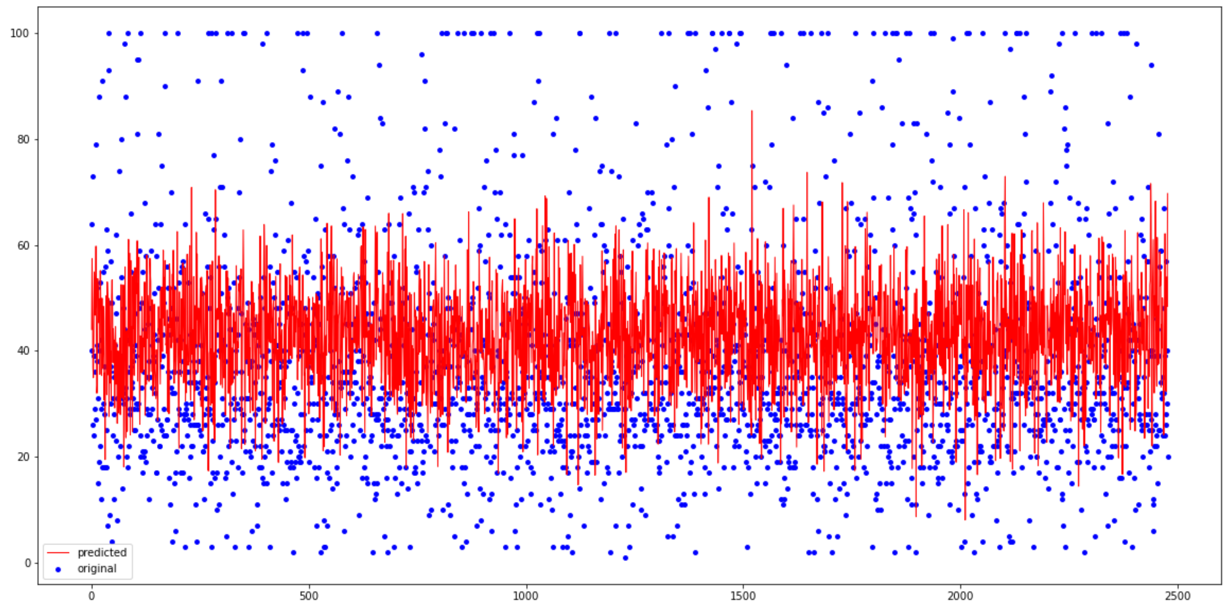


In [22]:
```
blurann = Sequential([
            Flatten(),
            Dense(1, activation='relu')
          ])

model_compfit(blurann, X_train_blur, y_train, 10)
```

```
Epoch 1/10
233/233 [==============================] - 1s 4ms/step - loss: 508.3556 - root_
mean_squared_error: 22.5467
Epoch 2/10
233/233 [==============================] - 1s 4ms/step - loss: 488.4328 - root_
mean_squared_error: 22.1005
Epoch 3/10
233/233 [==============================] - 1s 4ms/step - loss: 498.3028 - root_
mean_squared_error: 22.3227
Epoch 4/10
233/233 [==============================] - 1s 4ms/step - loss: 491.4557 - root_
mean_squared_error: 22.1688
Epoch 5/10
233/233 [==============================] - 1s 4ms/step - loss: 489.2918 - root_
mean_squared_error: 22.1199
Epoch 6/10
233/233 [==============================] - 1s 4ms/step - loss: 478.0587 - root_
mean_squared_error: 21.8646
Epoch 7/10
233/233 [==============================] - 1s 4ms/step - loss: 487.8592 - root_
mean_squared_error: 22.0875
Epoch 8/10
233/233 [==============================] - 1s 4ms/step - loss: 482.4075 - root_
mean_squared_error: 21.9638
Epoch 9/10
233/233 [==============================] - 1s 5ms/step - loss: 483.1240 - root_
mean_squared_error: 21.9801
Epoch 10/10
233/233 [==============================] - 2s 9ms/step - loss: 474.9717 - root_
mean_squared_error: 21.7938
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten_1 (Flatten)          (None, 49152)             0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 49153
=================================================================
Total params: 49,153
Trainable params: 49,153
Non-trainable params: 0
_________________________________________________________________
```

In [23]:
```
model_eval(blurann, X_train_blur, y_train, X_test, y_test, 'Blurred ANN')
```

```
233/233 [==============================] - 4s 19ms/step - loss: 470.5186 - root
_mean_squared_error: 21.6914
78/78 [==============================] - 1s 8ms/step - loss: 541.4640 - root_me
an_squared_error: 23.2694

    Blurred ANN Training Metrics:
    Loss: 470.519
    RMSE: 21.691
    ------
    Blurred ANN Test Metrics:
    Loss: 541.464
    RMSE: 23.269
```

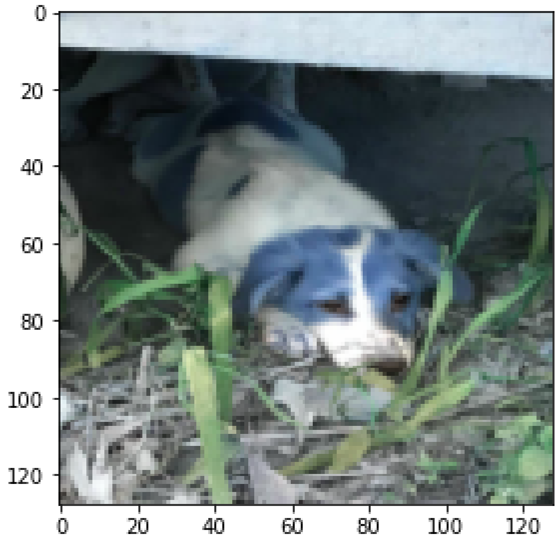


We then flip the images horizontally.

In [24]:
```
X_train_flip = []

for image in X_train:
    image = cv2.flip(image,1)
    X_train_flip.append(image)

X_train_flip = np.array(X_train_flip)
```

In [25]:
```
io.imshow(X_train_flip[0])
```

Out[25]:
```
<matplotlib.image.AxesImage at 0x7faa9d8b3a90>
```

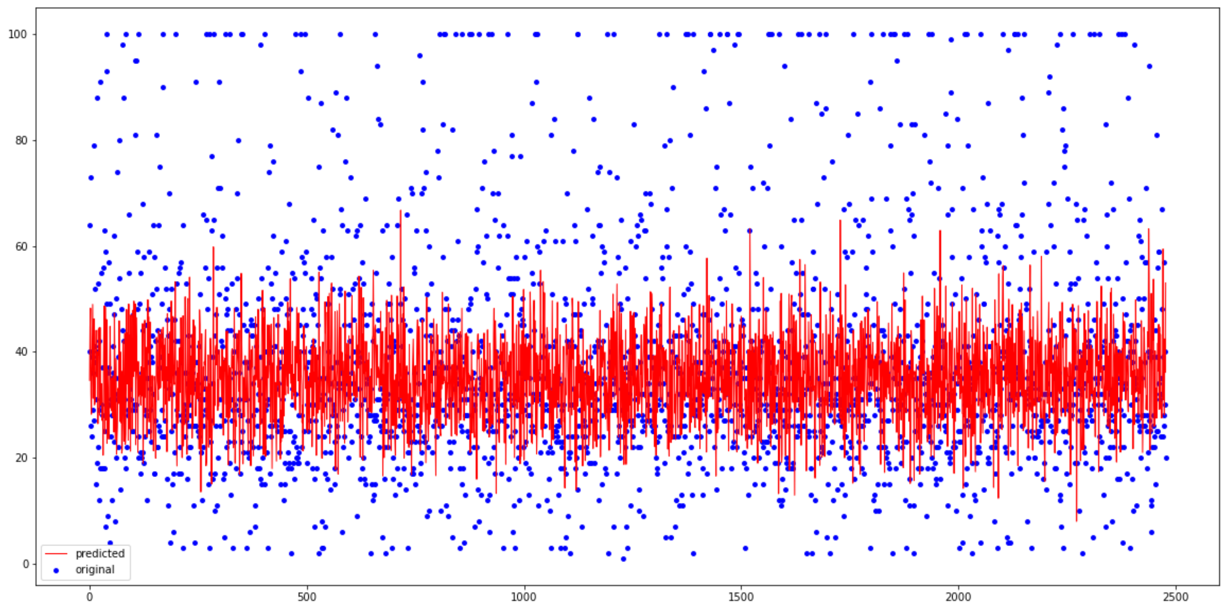


In [26]:
```
flipann = Sequential([
            Flatten(),
            Dense(1, activation='relu')
          ])

model_compfit(flipann, X_train_flip, y_train, 10)
```

```
Epoch 1/10
233/233 [==============================] - 1s 5ms/step - loss: 515.4820 - root_
mean_squared_error: 22.7042
Epoch 2/10
233/233 [==============================] - 1s 5ms/step - loss: 491.3006 - root_
mean_squared_error: 22.1653
Epoch 3/10
233/233 [==============================] - 1s 5ms/step - loss: 484.7204 - root_
mean_squared_error: 22.0164
Epoch 4/10
233/233 [==============================] - 1s 5ms/step - loss: 485.3916 - root_
mean_squared_error: 22.0316
Epoch 5/10
233/233 [==============================] - 1s 5ms/step - loss: 487.7504 - root_
mean_squared_error: 22.0851
Epoch 6/10
233/233 [==============================] - 1s 5ms/step - loss: 493.7435 - root_
mean_squared_error: 22.2203
Epoch 7/10
233/233 [==============================] - 1s 5ms/step - loss: 462.7820 - root_
mean_squared_error: 21.5124
Epoch 8/10
233/233 [==============================] - 1s 5ms/step - loss: 467.0221 - root_
mean_squared_error: 21.6107
Epoch 9/10
233/233 [==============================] - 1s 5ms/step - loss: 464.9805 - root_
mean_squared_error: 21.5634
Epoch 10/10
233/233 [==============================] - 1s 5ms/step - loss: 472.2879 - root_
mean_squared_error: 21.7322
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
flatten_2 (Flatten)          (None, 49152)             0         
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 49153     
=================================================================
Total params: 49,153
Trainable params: 49,153
Non-trainable params: 0
_________________________________________________________________
```

In [27]:
```
model_eval(flipann, X_train_flip, y_train, X_test, y_test, 'Flipped ANN')
```

```
233/233 [==============================] - 2s 8ms/step - loss: 429.9602 - root_
mean_squared_error: 20.7355
78/78 [==============================] - 1s 7ms/step - loss: 502.3939 - root_me
an_squared_error: 22.4141

    Flipped ANN Training Metrics:
    Loss: 429.96
    RMSE: 20.735
    ------
    Flipped ANN Test Metrics:
    Loss: 502.394
    RMSE: 22.414
```



Both types of image augmentation performed worse than our baseline.

Iterative Artificial Neural Networks

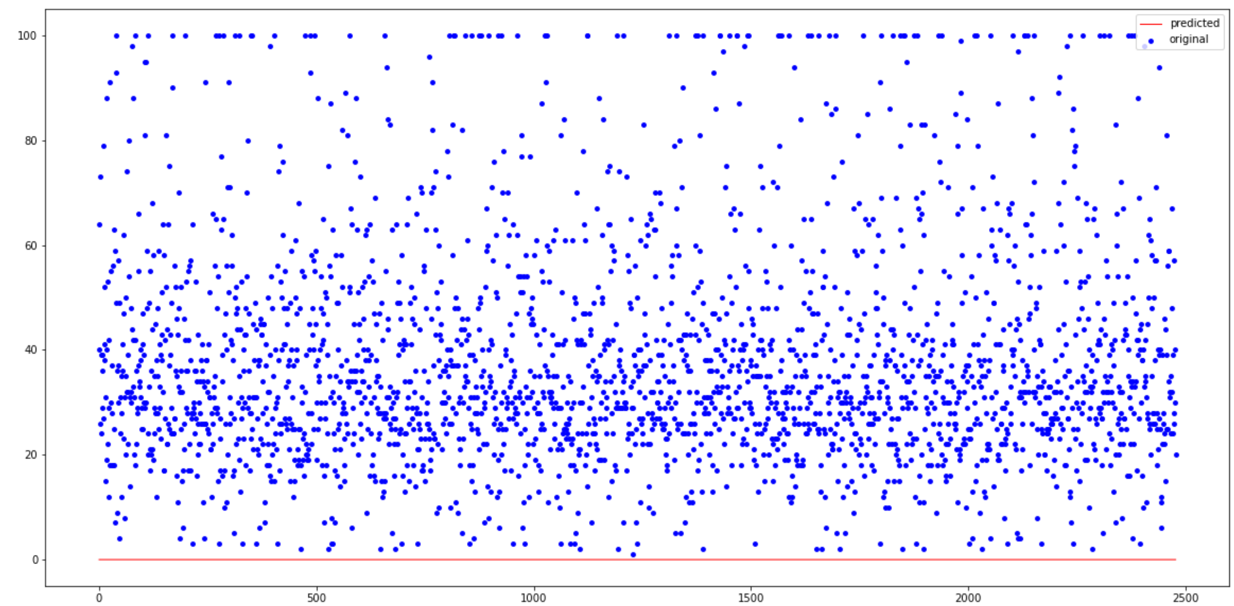
We move on to build more complex ANN models.

In [28]:
```
ann2 = Sequential([
        Flatten(),
        Dense(1000, activation='relu'),
        Dense(1, activation='relu')
      ])

model_compfit(ann2, X_train, y_train, 10)
```

```
Epoch 1/10
233/233 [==============================] - 87s 372ms/step - loss: 2517.0427 - r
oot_mean_squared_error: 50.1701
Epoch 2/10
233/233 [==============================] - 87s 373ms/step - loss: 1861.6760 - r
oot_mean_squared_error: 43.1471
Epoch 3/10
233/233 [==============================] - 81s 348ms/step - loss: 1861.6760 - r
oot_mean_squared_error: 43.1471
Epoch 4/10
233/233 [==============================] - 75s 320ms/step - loss: 1861.6760 - r
oot_mean_squared_error: 43.1471
Epoch 5/10
233/233 [==============================] - 72s 308ms/step - loss: 1861.6760 - r
oot_mean_squared_error: 43.1471
Epoch 6/10
233/233 [==============================] - 72s 310ms/step - loss: 1861.6760 - r
oot_mean_squared_error: 43.1471
Epoch 7/10
233/233 [==============================] - 72s 308ms/step - loss: 1861.6760 - r
oot_mean_squared_error: 43.1471
Epoch 8/10
233/233 [==============================] - 72s 308ms/step - loss: 1861.6760 - r
oot_mean_squared_error: 43.1471
Epoch 9/10
233/233 [==============================] - 72s 311ms/step - loss: 1861.6760 - r
oot_mean_squared_error: 43.1471
Epoch 10/10
233/233 [==============================] - 71s 306ms/step - loss: 1861.6760 - r
oot_mean_squared_error: 43.1471
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten_3 (Flatten)          (None, 49152)             0
_________________________________________________________________
dense_3 (Dense)              (None, 1000)              49153000
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 1001
=================================================================
Total params: 49,154,001
Trainable params: 49,154,001
Non-trainable params: 0
_________________________________________________________________
```

In [29]:
```
model_eval(ann2, X_train, y_train, X_test, y_test, 'Second ANN')
```

```
233/233 [==============================] - 23s 97ms/step - loss: 1861.6760 - ro
ot_mean_squared_error: 43.1471
78/78 [==============================] - 7s 96ms/step - loss: 1898.7963 - root_
mean_squared_error: 43.5752

    Second ANN Training Metrics:
    Loss: 1861.676
    RMSE: 43.147
    ------
    Second ANN Test Metrics:
    Loss: 1898.796
    RMSE: 43.575
```

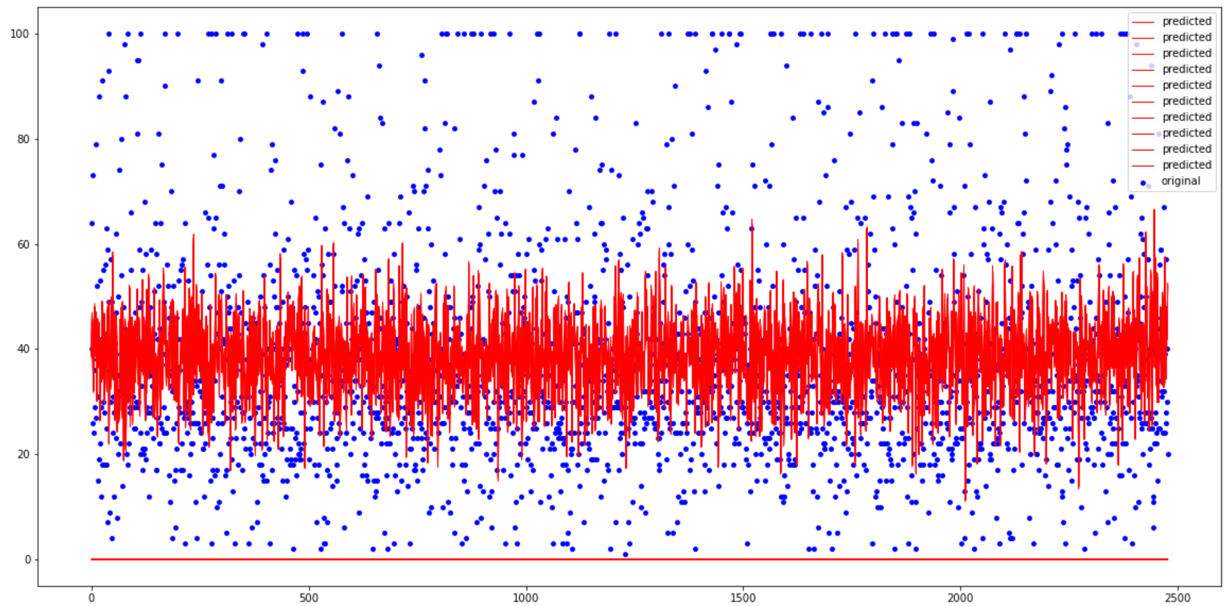


In [30]:
```
ann3 = Sequential([
        Flatten(),
        Dense(3000, activation='relu'),
        Dense(1000, activation='relu'),
        Dense(10, activation='relu')
      ])

model_compfit(ann3, X_train, y_train, 10)
```

```
Epoch 1/10
233/233 [==============================] - 207s 890ms/step - loss: 1239.5125 -
root_mean_squared_error: 35.2067
Epoch 2/10
233/233 [==============================] - 193s 830ms/step - loss: 1027.4346 -
root_mean_squared_error: 32.0536
Epoch 3/10
233/233 [==============================] - 199s 853ms/step - loss: 1026.6284 -
root_mean_squared_error: 32.0410
Epoch 4/10
233/233 [==============================] - 177s 759ms/step - loss: 1021.8079 -
root_mean_squared_error: 31.9657
Epoch 5/10
233/233 [==============================] - 166s 713ms/step - loss: 1017.9619 -
root_mean_squared_error: 31.9055
Epoch 6/10
233/233 [==============================] - 170s 729ms/step - loss: 1017.0810 -
root_mean_squared_error: 31.8917
Epoch 7/10
233/233 [==============================] - 166s 714ms/step - loss: 1013.6356 -
root_mean_squared_error: 31.8376
Epoch 8/10
233/233 [==============================] - 166s 714ms/step - loss: 1012.2665 -
root_mean_squared_error: 31.8161
Epoch 9/10
233/233 [==============================] - 166s 713ms/step - loss: 1008.4465 -
root_mean_squared_error: 31.7561
Epoch 10/10
233/233 [==============================] - 161s 690ms/step - loss: 1005.7928 -
root_mean_squared_error: 31.7142
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten_4 (Flatten)          (None, 49152)             0
_________________________________________________________________
dense_5 (Dense)              (None, 3000)              147459000
_________________________________________________________________
dense_6 (Dense)              (None, 1000)              3001000
_________________________________________________________________
dense_7 (Dense)              (None, 10)                10010
=================================================================
Total params: 150,470,010
Trainable params: 150,470,010
Non-trainable params: 0
_________________________________________________________________
```

In [31]:
```
model_eval(ann3, X_train, y_train, X_test, y_test, 'Third ANN')
```

```
233/233 [==============================] - 32s 138ms/step - loss: 995.3323 - ro
ot_mean_squared_error: 31.5489
78/78 [==============================] - 11s 138ms/step - loss: 1049.9214 - roo
t_mean_squared_error: 32.4025

    Third ANN Training Metrics:
    Loss: 995.332
    RMSE: 31.549
    ------
    Third ANN Test Metrics:
    Loss: 1049.921
    RMSE: 32.402
```

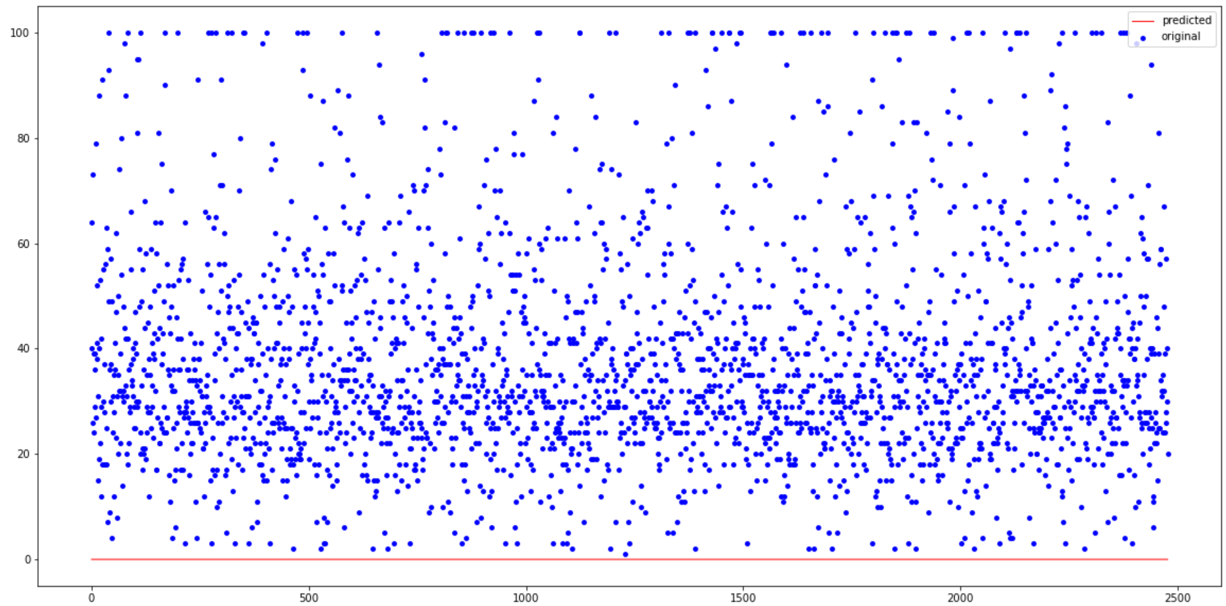


In [32]:
```
ann4 = Sequential([
        Flatten(),
        Dense(units=128, activation='relu'),
        Dense(units=1, activation='relu')
])

model_compfit(ann4, X_train, y_train, 10)
```

```
Epoch 1/10
233/233 [==============================] - 9s 39ms/step - loss: 1889.0084 - roo
t_mean_squared_error: 43.4627
Epoch 2/10
233/233 [==============================] - 8s 33ms/step - loss: 1861.6760 - roo
t_mean_squared_error: 43.1471
Epoch 3/10
233/233 [==============================] - 7s 31ms/step - loss: 1861.6760 - roo
t_mean_squared_error: 43.1471
Epoch 4/10
233/233 [==============================] - 7s 32ms/step - loss: 1861.6760 - roo
t_mean_squared_error: 43.1471
Epoch 5/10
233/233 [==============================] - 7s 32ms/step - loss: 1861.6760 - roo
t_mean_squared_error: 43.1471
Epoch 6/10
233/233 [==============================] - 8s 33ms/step - loss: 1861.6760 - roo
t_mean_squared_error: 43.1471
Epoch 7/10
233/233 [==============================] - 8s 32ms/step - loss: 1861.6760 - roo
t_mean_squared_error: 43.1471
Epoch 8/10
233/233 [==============================] - 7s 31ms/step - loss: 1861.6760 - roo
t_mean_squared_error: 43.1471
Epoch 9/10
233/233 [==============================] - 7s 30ms/step - loss: 1861.6760 - roo
t_mean_squared_error: 43.1471
Epoch 10/10
233/233 [==============================] - 7s 32ms/step - loss: 1861.6760 - roo
t_mean_squared_error: 43.1471
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten_5 (Flatten)          (None, 49152)             0
_________________________________________________________________
dense_8 (Dense)              (None, 128)               6291584
_________________________________________________________________
dense_9 (Dense)              (None, 1)                 129
=================================================================
Total params: 6,291,713
Trainable params: 6,291,713
Non-trainable params: 0
_________________________________________________________________
```

In [33]:
```
model_eval(ann4, X_train, y_train, X_test, y_test, 'Fourth ANN')
```

```
233/233 [==============================] - 4s 16ms/step - loss: 1861.6760 - roo
t_mean_squared_error: 43.1471
78/78 [==============================] - 2s 22ms/step - loss: 1898.7963 - root_
mean_squared_error: 43.5752

    Fourth ANN Training Metrics:
    Loss: 1861.676
    RMSE: 43.147
    ------
    Fourth ANN Test Metrics:
    Loss: 1898.796
    RMSE: 43.575
```

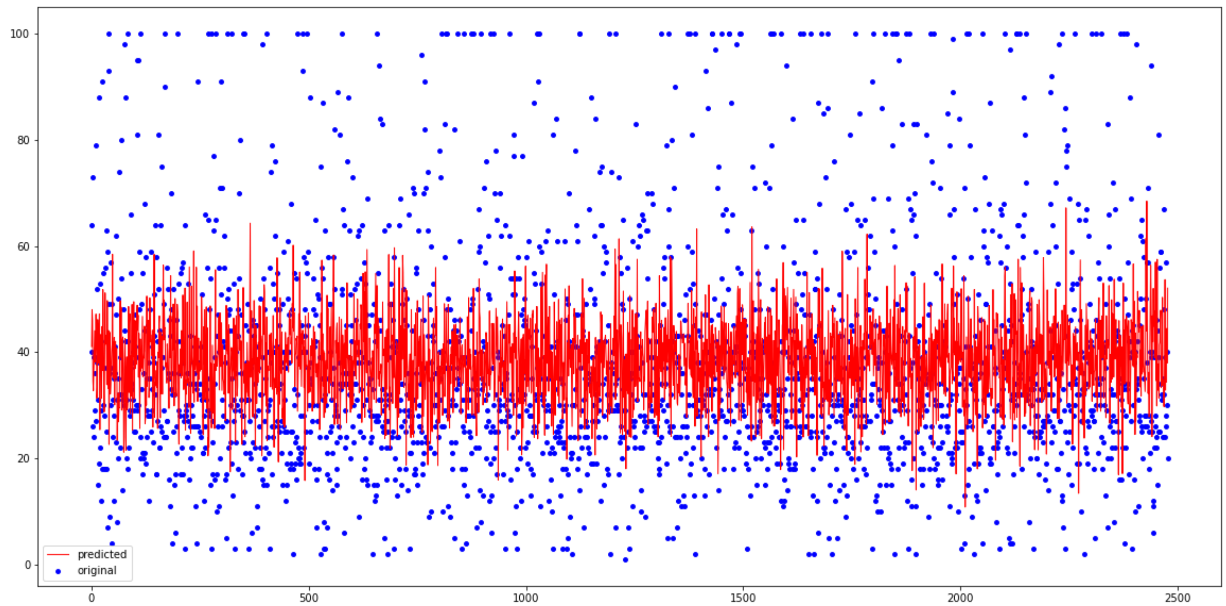


In [35]:
```
ann5 = tf.keras.Sequential([
        Flatten(),
        Dense(units=128, activation='relu'),
        Dense(units=64, activation='relu'),
        Dense(units=1, activation='relu')
])

model_compfit(ann5, X_train, y_train, 10)
```

```
Epoch 1/10
233/233 [==============================] - 11s 48ms/step - loss: 516.1583 - roo
t_mean_squared_error: 22.7191
Epoch 2/10
233/233 [==============================] - 13s 58ms/step - loss: 482.3322 - roo
t_mean_squared_error: 21.9621
Epoch 3/10
233/233 [==============================] - 23s 101ms/step - loss: 469.8159 - ro
ot_mean_squared_error: 21.6752
Epoch 4/10
233/233 [==============================] - 17s 74ms/step - loss: 473.5893 - roo
t_mean_squared_error: 21.7621
Epoch 5/10
233/233 [==============================] - 14s 59ms/step - loss: 467.6059 - roo
t_mean_squared_error: 21.6242
Epoch 6/10
233/233 [==============================] - 18s 76ms/step - loss: 452.8302 - roo
t_mean_squared_error: 21.2798
Epoch 7/10
233/233 [==============================] - 13s 56ms/step - loss: 456.5316 - roo
t_mean_squared_error: 21.3666
Epoch 8/10
233/233 [==============================] - 12s 50ms/step - loss: 447.3635 - roo
t_mean_squared_error: 21.1510
Epoch 9/10
233/233 [==============================] - 12s 51ms/step - loss: 445.7745 - roo
t_mean_squared_error: 21.1134
Epoch 10/10
233/233 [==============================] - 12s 50ms/step - loss: 442.9835 - roo
t_mean_squared_error: 21.0472
Model: "sequential_7"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
flatten_7 (Flatten)          (None, 49152)             0         
_________________________________________________________________
dense_13 (Dense)             (None, 128)               6291584   
_________________________________________________________________
dense_14 (Dense)             (None, 64)                8256      
_________________________________________________________________
dense_15 (Dense)             (None, 1)                 65        
=================================================================
Total params: 6,299,905
Trainable params: 6,299,905
Non-trainable params: 0
_________________________________________________________________
```

In [36]:
```
model_eval(ann5, X_train, y_train, X_test, y_test, 'Fifth ANN')
```

```
233/233 [==============================] - 8s 36ms/step - loss: 429.5197 - root
_mean_squared_error: 20.7249
78/78 [==============================] - 1s 19ms/step - loss: 487.1628 - root_m
ean_squared_error: 22.0718

    Fifth ANN Training Metrics:
    Loss: 429.52
    RMSE: 20.725
    ------
    Fifth ANN Test Metrics:
    Loss: 487.163
    RMSE: 22.072
```



We made five total ANN models, and they all performed worse than the baseline.

Iterative Convolutional Neural Networks

We move on to making Convolutional Neural Network models, hoping to do better than our baseline.

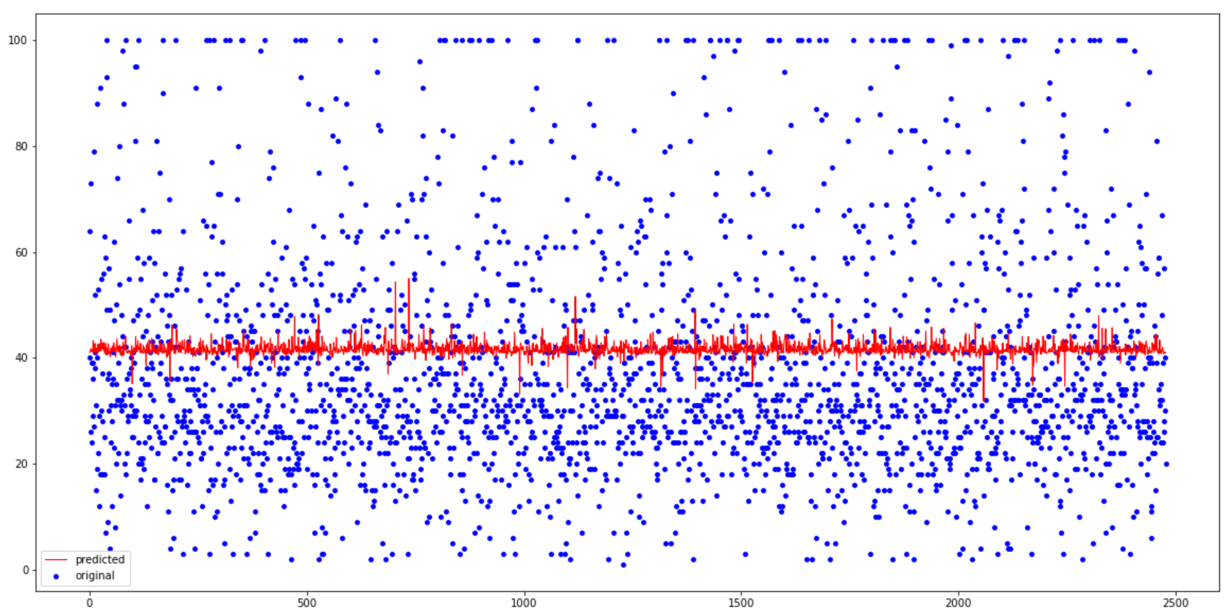
In [37]:
```
CNN = Sequential([
        Conv2D(32, (3, 3), activation='relu'),
        MaxPooling2D((2, 2)),
        Conv2D(32, (4, 4), activation='relu'),
        MaxPooling2D((2, 2)),
        Conv2D(64, (3, 3), activation='relu'),
        MaxPooling2D((2, 2)),
        Flatten(),
        Dense(128, activation='relu'),
        Dense(64, activation='relu'),
        Dense(1, activation='relu'),
])

model_compfit(CNN, X_train, y_train, 10)
```

```
Epoch 1/10
233/233 [==============================] - 202s 869ms/step - loss: 487.6511 -
root_mean_squared_error: 22.0828
Epoch 2/10
233/233 [==============================] - 159s 683ms/step - loss: 432.6213 -
root_mean_squared_error: 20.7995
Epoch 3/10
233/233 [==============================] - 159s 680ms/step - loss: 428.8285 -
root_mean_squared_error: 20.7082
Epoch 4/10
233/233 [==============================] - 154s 659ms/step - loss: 427.0878 -
root_mean_squared_error: 20.6661
Epoch 5/10
233/233 [==============================] - 160s 686ms/step - loss: 424.5081 -
root_mean_squared_error: 20.6036
Epoch 6/10
233/233 [==============================] - 211s 906ms/step - loss: 423.5745 -
root_mean_squared_error: 20.5809
Epoch 7/10
233/233 [==============================] - 153s 656ms/step - loss: 420.7753 -
root_mean_squared_error: 20.5128
Epoch 8/10
233/233 [==============================] - 151s 646ms/step - loss: 422.0416 -
root_mean_squared_error: 20.5437
Epoch 9/10
233/233 [==============================] - 153s 657ms/step - loss: 421.1585 -
root_mean_squared_error: 20.5221
Epoch 10/10
233/233 [==============================] - 147s 632ms/step - loss: 419.6141 -
root_mean_squared_error: 20.4845
Model: "sequential_8"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
conv2d (Conv2D)             (None, 126, 126, 32)      896

_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 63, 63, 32)       0

_________________________________________________________________
conv2d_1 (Conv2D)           (None, 60, 60, 32)        16416

_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 30, 30, 32)       0
```

```
conv2d_2 (Conv2D)            (None, 28, 28, 64)        18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 14, 14, 64)        0
_________________________________________________________________
flatten_8 (Flatten)          (None, 12544)             0
_________________________________________________________________
dense_16 (Dense)             (None, 128)               1605760
_________________________________________________________________
dense_17 (Dense)             (None, 64)                8256
_________________________________________________________________
dense_18 (Dense)             (None, 1)                 65
=================================================================
Total params: 1,649,889
Trainable params: 1,649,889
Non-trainable params: 0
_________________________________________________________________
```

In [44]:
```
model_eval(CNN, X_train, y_train, X_test, y_test, 'First CNN')
```

```
233/233 [==============================] - 30s 127ms/step - loss: 425.6042 - ro
ot_mean_squared_error: 20.6302
78/78 [==============================] - 11s 142ms/step - loss: 459.9646 - root
_mean_squared_error: 21.4468

    First CNN Training Metrics:
    Loss: 425.604
    RMSE: 20.63
    ------
    First CNN Test Metrics:
    Loss: 459.965
    RMSE: 21.447
```



In [45]:
```
CNN2 = Sequential([
        Conv2D(32, (3, 3), activation='relu'),
        MaxPooling2D((2, 2)),
        Flatten(),
        Dense(128, activation='relu'),
        Dense(64, activation='relu'),
        Dense(1, activation='relu'),
])

model_compfit(CNN2, X_train, y_train, 10)
```

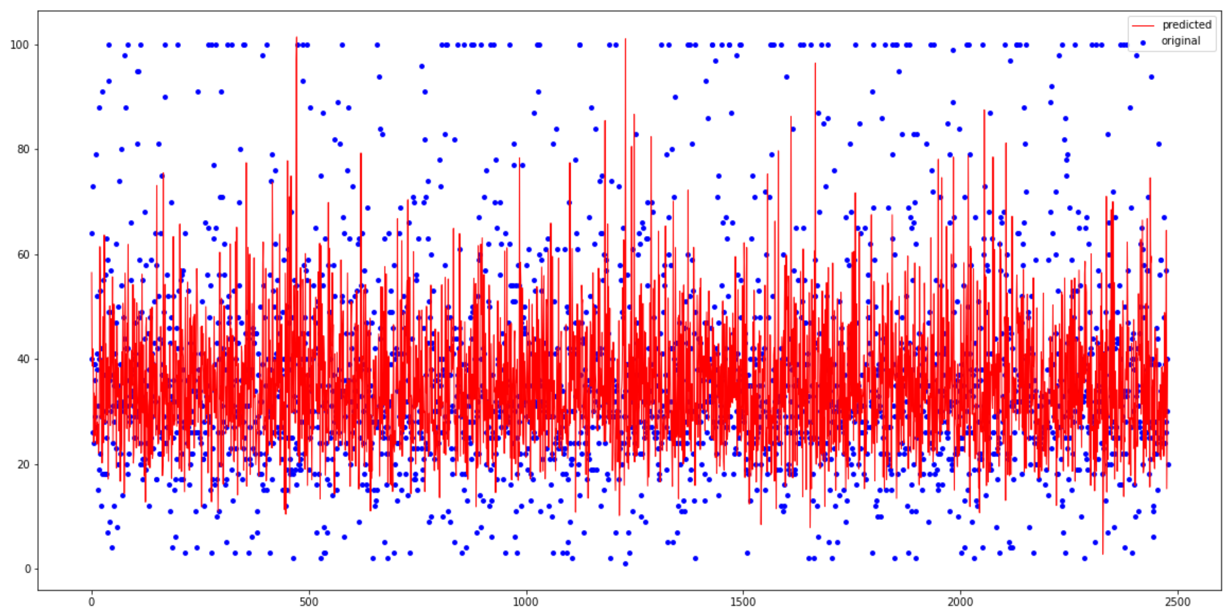
```
Epoch 1/10
233/233 [==============================] - 87s 374ms/step - loss: 479.8156 - ro
ot_mean_squared_error: 21.9047
Epoch 2/10
233/233 [==============================] - 83s 355ms/step - loss: 434.9066 - ro
ot_mean_squared_error: 20.8544
Epoch 3/10
233/233 [==============================] - 79s 337ms/step - loss: 424.2919 - ro
ot_mean_squared_error: 20.5983
Epoch 4/10
233/233 [==============================] - 80s 343ms/step - loss: 403.6696 - ro
ot_mean_squared_error: 20.0915
Epoch 5/10
233/233 [==============================] - 80s 344ms/step - loss: 379.1942 - ro
ot_mean_squared_error: 19.4729
Epoch 6/10
233/233 [==============================] - 73s 314ms/step - loss: 329.8124 - ro
ot_mean_squared_error: 18.1607
Epoch 7/10
233/233 [==============================] - 73s 313ms/step - loss: 266.5419 - ro
ot_mean_squared_error: 16.3261
Epoch 8/10
233/233 [==============================] - 75s 320ms/step - loss: 214.0641 - ro
ot_mean_squared_error: 14.6309
Epoch 9/10
233/233 [==============================] - 74s 317ms/step - loss: 161.1557 - ro
ot_mean_squared_error: 12.6947
Epoch 10/10
233/233 [==============================] - 73s 312ms/step - loss: 112.3282 - ro
ot_mean_squared_error: 10.5985
Model: "sequential_11"
```

Layer (type)	Output Shape	Param #
conv2d_5 (Conv2D)	(None, 126, 126, 32)	896
max_pooling2d_6 (MaxPooling2	(None, 63, 63, 32)	0
flatten_11 (Flatten)	(None, 127008)	0
dense_25 (Dense)	(None, 128)	16257152
dense_26 (Dense)	(None, 64)	8256
dense_27 (Dense)	(None, 1)	65

```
=================================================================
Total params: 16,266,369
Trainable params: 16,266,369
Non-trainable params: 0
_________________________________________________________________
```

In [51]:
```
model_eval(CNN2, X_train, y_train, X_test, y_test, 'Second CNN')
```

```
233/233 [==============================] - 34s 147ms/step - loss: 74.1564 - roo
t_mean_squared_error: 8.6114
78/78 [==============================] - 9s 118ms/step - loss: 602.0927 - root_
mean_squared_error: 24.5376

    Second CNN Training Metrics:
    Loss: 74.156
    RMSE: 8.611
    ------
    Second CNN Test Metrics:
    Loss: 602.093
    RMSE: 24.538
```



In [52]:
```
CNN3 = Sequential([
        Conv2D(32, (3, 3), activation='relu'),
        MaxPooling2D((2, 2)),
        Dense(128, activation='relu'),
        Dropout(0.25),
        Dense(64, activation='relu'),
        MaxPooling2D(pool_size=(2, 2)),
        Flatten(),
        Dropout(0.5),
        Dense(1, activation=None),
])

model_compfit(CNN3, X_train, y_train, 10)
```

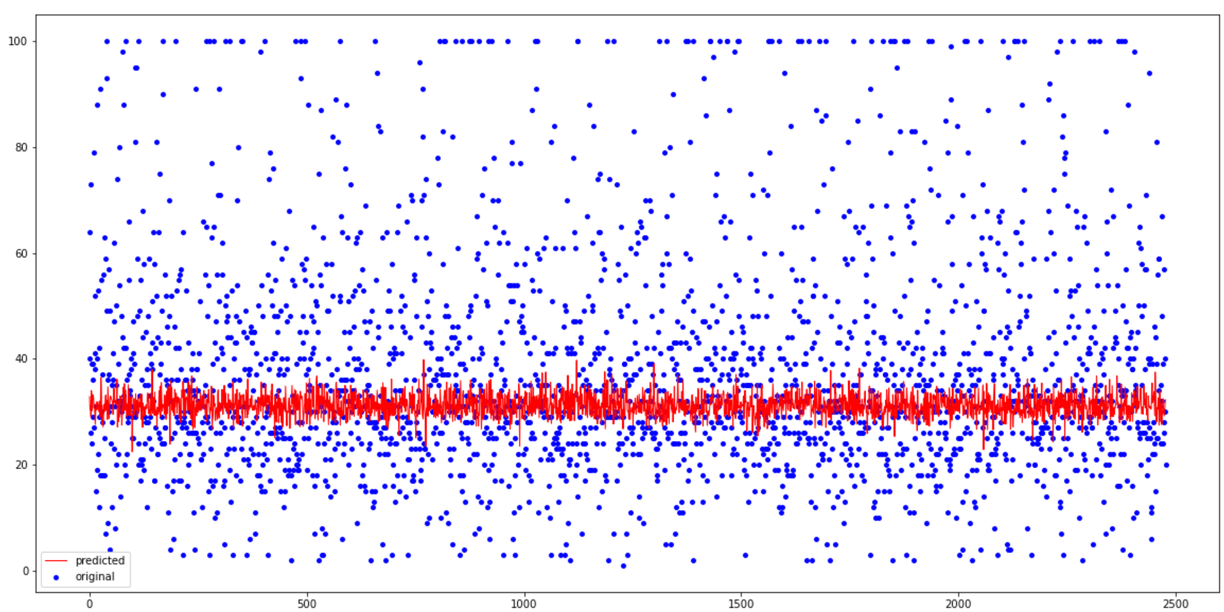
```
Epoch 1/10
233/233 [==============================] - 194s 835ms/step - loss: 458.8270 - r
oot_mean_squared_error: 21.4202
Epoch 2/10
233/233 [==============================] - 167s 718ms/step - loss: 427.9318 - r
oot_mean_squared_error: 20.6865
Epoch 3/10
233/233 [==============================] - 155s 666ms/step - loss: 423.3220 - r
oot_mean_squared_error: 20.5748
Epoch 4/10
233/233 [==============================] - 156s 667ms/step - loss: 424.7882 - r
oot_mean_squared_error: 20.6104
Epoch 5/10
233/233 [==============================] - 156s 669ms/step - loss: 421.2358 - r
oot_mean_squared_error: 20.5240
Epoch 6/10
233/233 [==============================] - 158s 680ms/step - loss: 420.5063 - r
oot_mean_squared_error: 20.5063
Epoch 7/10
233/233 [==============================] - 157s 675ms/step - loss: 424.1791 - r
oot_mean_squared_error: 20.5956
Epoch 8/10
233/233 [==============================] - 156s 668ms/step - loss: 417.7438 - r
oot_mean_squared_error: 20.4388
Epoch 9/10
233/233 [==============================] - 153s 655ms/step - loss: 416.7375 - r
oot_mean_squared_error: 20.4142
Epoch 10/10
233/233 [==============================] - 159s 681ms/step - loss: 414.6174 - r
oot_mean_squared_error: 20.3622
Model: "sequential_14"
```

Layer (type)	Output Shape	Param #
conv2d_8 (Conv2D)	(None, 126, 126, 32)	896
max_pooling2d_11 (MaxPooling	(None, 63, 63, 32)	0
dense_34 (Dense)	(None, 63, 63, 128)	4224
dropout_6 (Dropout)	(None, 63, 63, 128)	0
dense_35 (Dense)	(None, 63, 63, 64)	8256

```
max_pooling2d_12 (MaxPooling (None, 31, 31, 64)         0
_________________________________________________________________
flatten_14 (Flatten)         (None, 61504)              0
_________________________________________________________________
dropout_7 (Dropout)          (None, 61504)              0
_________________________________________________________________
dense_36 (Dense)             (None, 1)                  61505
=================================================================
Total params: 74,881
Trainable params: 74,881
Non-trainable params: 0
_________________________________________________________________
```

In [53]:
```python
model_eval(CNN3, X_train, y_train, X_test, y_test, 'Third CNN')
```

```
233/233 [==============================] - 47s 201ms/step - loss: 451.8073 - ro
ot_mean_squared_error: 21.2558
78/78 [==============================] - 14s 186ms/step - loss: 500.4067 - root
_mean_squared_error: 22.3698

    Third CNN Training Metrics:
    Loss: 451.807
    RMSE: 21.256
    ------
    Third CNN Test Metrics:
    Loss: 500.407
    RMSE: 22.37
```



After running these 3 CNN models, we were not able to improve our RMSE from the baseline.

Conclusion

> We attempted Data Augmentation but found that Blurring and Flipping the images did not improve our RMSE.
>
> One big concern for us was that how `Pawpularity` was determined was unclear. There wasn't much information on the Kaggle competition description that explained how the score was created and how to interpret it. We know the scale is from 1-100, but do all the images with a score of 100 have the same amount of traffic? We think understanding how `Pawpularity` is scored would help us prepare the data for better model results.
>
> As we only had three days to complete this project, this is the best we could do.

Next Steps

> First, we would look into what goes into determining `Pawpularity` . Another thing we would like to look into would be features other than photos that affect pet profile traffic such as age of the animal and time they've been up for adoption. Lastly, our knowledge of neural networks is limited, and so, given more time, we would have liked to explore further.

Sources

- [Kaggle Competition Dataset (https://www.kaggle.com/c/petfinder-pawpularity-score)](https://www.kaggle.com/c/petfinder-pawpularity-score)
- [Photo Metadata (https://github.com/stevenaddison/Project-4/blob/main/data/metadata.md)](https://github.com/stevenaddison/Project-4/blob/main/data/metadata.md)
- [Speed of Dog Adoption: Impact of Online Photo Traits (https://www.tandfonline.com/doi/full/10.1080/10888705.2014.982796)](https://www.tandfonline.com/doi/full/10.1080/10888705.2014.982796)