Domain Analysis

MammalWeb: System currently in place

MammalWeb's purpose is to collect information about wildlife in the UK and allow biological scientists to form conclusions about the ecosystem on both the national and local scale. This information can then be used to inform decisions about conservation projects, culling action and similar activities that affect wildlife and the environment.

The front end of MammalWeb at the moment is the website MammalWeb.org on which users can upload images from camera traps that they have set up in their local area. Anyone can then sign on as a 'spotter' and classify images drawn from the all those that have been uploaded. The classifications (species present and age/gender/number if relevant) are then stored in a database.

Currently, extracting useful information from these classifications is not well implemented - the data dump we recieved contained data from a little over 20000 photos with nearly 90000 individual classifications and there is no automated system in place for removing 'bad' information and condensing the useful data into a form that is easier to use for the biologists. Any use of the collected data so far has been done by manually parsing the data.

We have been provided with an algorithm designed to aggregate data collected in citizen scientist projects. The algorithm, outlined in Swanson et al. (2015), creates an aggregate classification equal to the most common choice from all the individual classifications. For example, if 8 classification of deer, 3 of horse and 1 of nothing here have been recorded then the Swanson algorithm will say that the photo is of a deer. 3 metrics to show how likely the classification is to be correct are then calculated-

1. Evenness: All non-blank classifications are used in Pielou’s eveness index to calculate this. The formula is where S is the number of different species classified as being present (2 in the example given) and pi is the proportion of total classifications for species i (8/11 and 3/11 in the example- remember that blanks are ignored here). This comes out as 0.845 for the example. If only one species is classified, the result will be 0 and the highest possible result is 1 so a relatively high result like 0.845 can be interpreted as high uncertainty that the aggregate classification is wrong.
2. Fraction blanks: The fraction of “nothing here” classifications for an image that has an aggregate classification that is not “nothing”. The above example would have fractional blanks of 1/12
3. Fraction support: The fraction of classifications that support the aggregate answer (in the above example it would be 2/3)

In general, the Swanson paper says that the number of classifications required for an accurate aggregate answer is quite low. For easy to identify species, after only around 3 classifications the aggregate answer has an extremely high level of accuracy if the evenness is low. For more difficult species after around 10 classifications the aggregate is fairly likely to be accurate, but for these species even increasing the number of classifications does not improve the aggregate’s likelihood of being correct very much. We have not been given a ‘gold standard’ set of data so calculating which species are easy and which are difficult will not be possible. The paper focuses on images that only contain a single species of animal for ease of measuring how accurate the algorithm is, but does say that if two species are present then simply take both the most and second most identified species as the overall aggregate. Other specifics to consider are when there are ‘enough’ classifications on a picture to give satisfactorily accurate metrics and when to discard an image as having nothing in it (The suggested boundary is 5 blank classifications in a row).

Related systems

A closely related system would be Snapshot Serengeti (SS) where a very similar system of uploading and classifying camera trap photos by citizen scientists is in place. There are a series of blog posts by Margaret Kosmala (beginning here[[1]](#footnote-1)) that give good insight on how they went about improving the performance of their algorithm. SS went through a couple of slight variants for their plurality algorithm, but is overall very similar to what we are going to implement.

Initially, a species was made the aggregate classification if it had >=50% of the overall classifications. This gave a classification for 96% of the images captured where 57% were unanimous and 84% had at least ¾ fraction support. A later refinement of the algorithm[[2]](#footnote-2) made it closer to what we will be using by saying that the most picked animal was classified as the aggregate classification ie. If there were 10 Impala, 4 Thomson Gazelle and 7 Dik Dik classifications, the older version of the algorithm would not give an aggregate answer but the newer one (and Swanson’s) would say that the photo was of an impala. This meant that almost 97% of images received a classification but there were a few more errors- of the images that were not classified by the old algorithm but were by the new, 57% were correct when compared with the expert data set.

Important things to note about SS’ plurality algorithm is that they had a group of experts create a set of definite classifications and the algorithm agreed with these expert classifications on 95.8% of photos. This is similar to the certainty percentages given by Swanson for the results of his algorithm. Another potentially important point is that all of the images used for aggregate classifications had received at least 10 separate classifications. Initially photos with less than this were used however it led to very inaccurate results for some photos where animals that weren’t present were nevertheless identified as being there. The number of classifications for images on MammalWeb is significantly lower than for SS so defining boundaries of when a classification should be considered definite is probably something we need to experiment with.

1. http://blog.snapshotserengeti.org/2013/01/30/some-results-from-season-4/ [↑](#footnote-ref-1)
2. http://blog.snapshotserengeti.org/2013/06/07/majority-rules-algorithm/ [↑](#footnote-ref-2)