Use Cases: Validation Report First Evaluation 2015

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Documentation Information

Project (Title/Number)	MICO - “Media in Context” (610480)
Work Package / Task	Work Package 7 - Use Case: Crowd Sourcing Platform Work Package 8 - Use Case: Video Sharing Platform
Responsible person and project partner	Chris Lintott (University of Oxford - Zooniverse) Andrea Volpini (InsideOut10)

Executive Summary

This document outlines the Test Plan (First Evaluation) describing the setup of the first evaluation round in the two use cases (WP7 and WP8) and the functionalities that are evaluated. It is currently restricted to the testing conducted during the development of the MICO platform. The aim is to compare each MICO Technology Enabler (TE) prior to beginning end-to-end testing of the system.

For each MICO TE included in these tests we will assess the following:

1. **output accuracy** - how accurate, detailed and meaningful each single response is when compared to our best estimates using our existing databases and analysis;
2. **technical performance** - how much time each task requires and how scalable the solution is when we increase in volume the amount of contents being analysed;
3. **usability** evaluated both in terms of **integration, modularity** and **usefulness**.

For Zooniverse, testing focussed on evaluation of the animal/emptiness detectors via the MICO Platform API (TE-202), and on validation of the user profile generator and subject recommender first through functional testing and later through using them in an experimental scenario (TE-506).

TE-202 was tested using a test harness to process 50,270 images through the platform and collect and analyse the results, specifically in terms of Precision, Recall and F1 Score. We had originally planned to analyse 300,000 images but due to issues with the deployed platform instance and long periods of downtime we had to use a reduced dataset. Findings were that the MICO platform is very precise at emptiness detection (84%), though recall is much lower (44%). Nonetheless this result is immediately useful for Zooniverse and can save several days of volunteer effort on a project. The platform's performance for animal counting and species identification was less successful. We saw high recall for ostrich detection and high precision for wildebeest detection, however we suspect these results are caused by the prevalence of wildebeest and the rarity of ostriches in the dataset. Emptiness detection was more precise in the daytime, but animal counting was more precise at night. The complexity of an image, and the mix of species present, did not make much impact on the detectors, though multi-species images generally performed slightly better, perhaps benefitting from the input of multiple detectors. In this report we also analyse the testing approach used so that we can improve our approach next time.

TE-506 did not proceed as planned, as the Zaizi solution did not materialise. However a script based approach was used by Zooniverse to generate subject content and species preference data for user profiles. This approach is validated and detailed below. The user profiles and subject recommendation routines were used in an experimental scenario, the "Happy User Experiment", which is detailed on the MICO blog. This work made a significant infrastructure

contribution to Zooniverse, as Zooniverse now has a user behaviour collector and experiment management system that can be used in future experiments. The experiment found that providing users with “preferred” species did not encourage greater participation, in fact it deterred users and they left sooner. This was investigated further and lead to new findings that the impact of blank images in a user’s image set can have a strong impact on engagement. These findings are being published at HCOMP 2015 and further details and links are provided below.

For InsideOut10 we’ve downsized the ambitions of our validation by focusing on:

- only two extractors (TE-204 face detection and TE-214 automatic speech recognition)
    - the media quality TE-205 and is also available in the system but we cannot yet access the results in a useful way
    - the temporal video segmentation TE-206 is available in the system and has been integrated in a live scenario but it is not part of this evaluation
- a controlled evaluation of the results in terms of precision, recall and F1 measure conducted in our lab without engaging (other than for gathering the datasets and sharing the results) our stakeholders Greenpeace and Shoof. From the original plan of running the evaluation *with them* by integrating MICO in our existing workflows we had to keep the validation “internal” for time constraint (extractors have been released beyond the expected or planned date due to the complexity of the overall project).
- a limited amount of data to be analyzed and processed (60 images and 10 videos)
- a specific use-case for WP5 and an *internal evaluation*. The direction here is taken and the work has been progressing regardless of the changes in the leadership team of this work package. As now - at least for our showcase - with the work done on prediction.io there seems to be a valuable approach to cross-media reccomendations. Unfortunately we could not complete the a/b testing with our test group as expected and the analysis is the result of an *internal analysis* (conducted with the support of the team from Fraunhofer).

On the positive front we’ve seen face detection providing results of immediate use and overall comparable with the results of the analysis provided by commercial service providers (this is particularly true for in-front face detections). This is indeed a great outcome for MICO and a clear evidence that the work done on the extractors is consistent and *state-of-the-art*.

We’ve also seen the value of orchestrating different extractors when for instance analyzing audio-visual contents: a face detection running after the temporal video segmentation is definitely more useful - while harder to evaluate in terms of precision/recall - than running the extractor by itself on all image stills (when bringing the results of the analysis back to the end-user the application developer needs to control and limit the amount of information provided via the user interface).

On TE-214 (automatic speech recognition) MICO by splitting automatically a video in audio and video parts is quite effective in terms of workflow but, as of today, lacks solid language models to compete (even on British English) with commercially available solutions - this was somehow expected and can be improved with more training data.

While waiting for all components of MICO to be finalized we've prepared a good integration infrastructure for extending the use of MICO to our various community of prospects and stakeholders.

This work also serve as a good base for integrators working in *JAVA* (the code has been contributed as open source and it is available on GitHub). The infrastructure developed is also intended for the vast WordPress community (25% of all existing websites according to the latest W3Techs report) interested in media analysis and recommendations.

Last but not least we've build a tool for evaluating the results of the analysis of MICO on images and for creating the ground data (manual annotations) - this methodology and approach can be re-used on the next iterations of these tests.

A1: Zooniverse Showcase - Validation per Test Plan

Goals of Test Plan

The goals of the test plan were stated thus:

We aim to compare each MICO TE prior to beginning end-to-end testing of the system. For each MICO TE included in these tests we will assess the following:

4. **output accuracy** - how accurate, detailed and meaningful each single response is when compared to our best estimates using our existing databases and analysis;
5. **technical performance** - how much time each task requires and how scalable the solution is when we increase in volume the amount of contents being analysed;
6. **usability** evaluated both in terms of **integration, modularity** and **usefulness**.

It was noted in the test plan, and we note again here, that a low score on these metrics does not indicate a failure. It is important to collect these metrics to correctly understand what the system does and does not do - but this does not constitute a success/fail judgement of the platform as a whole.

Test Implementation Plan

To recap, the test plan for Zooniverse was as follows:

ID	Test	Description
TP-202-01	**Test emptiness detection across a season of subjects**	• use dataset **TD-12** • process **TD-12** with TE-202(emptiness detector) • calculate precision, recall and F1-measure on **TE-202** outputs. • calculate manual blanks, for **TD-12** per normalization procedure. • calculate precision, recall and F1-measure on outputs. • compare **KPIs**
TP-202-02	**Test animal type detection across a season of subjects**	• use dataset **TD-12** • process **TD-12** with TE-202(group detector) • calculate precision, recall and F1-measure on **TE-202** outputs. • calculate manual animal types present, for **TD-12** per normalization procedure. • calculate precision, recall and F1-measure on outputs. • compare **KPIs**
TP-202-03	**Test animal counting across a season of subjects**	• use dataset **TD-12** • process **TD-12** with TE-202(animal detector) • calculate precision, recall and F1-measure on **TE-202** outputs. • calculate manual animal counts for **TD-12** per normalization procedure. • calculate precision, recall and F1-measure on outputs. • compare **KPIs**
TP-506-01	**Test species recommended in recommended images**	• use dataset **TD-14** • Train **TE-506** (recommendation engine) with TD-14. • calculate precision, recall and F1-measure on **TE-506** outputs. • Process results from TE-506 per user against TD-16, and identify distinct species that were recommended to each user. • Compare species recommendation to TD-14 preferences. • Assess KPIs
TP-506-02	**Test subjects recommended**	• use dataset **TD-14** • Train **TE-506** (recommendation engine) with **TD-14**. • calculate precision, recall and F1-measure on **TE-506** outputs.
TP-506-03	**Test subjects recommended**	• use dataset **TD-15** • Train **TE-506** (recommendation engine) with **TD-15**. • compare recommended subjects to those in TP-506-02 - ensure the correct species are displaced according to the changes that were made between TD-14 & TD-15 • assess **KPIs**
TP-506-04	**Real-world tests using recommender results**	• use dataset **TD-11** • Run a full experiment over a period of days/weeks, per the Happy User Experiment plans, inserting recommended images per user. • Evaluate session times and number of classifications for experimental vs control user. • Determine whether the recommended images increased or decreased user participation. • assess **KPIs**

A2: Zooniverse Showcase - Validation Report

The following metrics will be used:

Technical performance

Technical performance will be measured in terms of:

- **latency** - time required to perform a single task on a given dataset. Measures will be repeated 10 times;
- **scalability** - an assessment of whether the given TE is suitably efficient and practical when applied to large situations (e.g. a large input dataset and / or, a large number concurrent requests)

Usability

The TE usability requires a qualitative evaluation which will consider:

- **integration** - how simple it is to integrate each single TE into Zooniverse technologies;
- **modularity** - how simple it is to configure each TE and/or a combination of multiple TEs in a chain from within pre-existent application workflows.
- **usefulness** - looking at the degree to which the TE delivers valuable information and tools that Zooniverse applications will be able to harness in future, and some consideration towards a cost-benefit analysis of doing so.

Overview of Test Results

ID	Test	Summary of Results
TP-202-01	**Test emptiness detection across a season of subjects**	• Overall, precision was high (84%) and recall was low (45%) • We see a tendency to over classify, which for the Zooniverse use case is actually preferable over false negatives. • MICO seems to be much more precise at determining blanks during the day than at night. Recall doesn't vary much between day and night. • Most importantly, **this new capability to detect blanks is immediately useful to Zooniverse, and can save Zooniverse over 115,000 classifications on a 300,000 image dataset - several days to a week of volunteer effort.**
TP-202-02	**Test animal type detection across a season of subjects**	• Precision was very low (around 6%), though about 10% better for wildebeest. • Ostriches achieved a high recall (61%) though we think this is solely due to overdetection of ostriches across all images combined with ostriches being very rare in the dataset. • Wildebeest detection seemed to perform much better (69% precision) in complex images than in simple images (30% precision). We think this is explained by overdetection of wildebeest across all images combined with wildebeest being especially prevalent in the dataset.

TP-202-03	**Test animal counting across a season of subjects**	• Both precision and recall were uniformly very low. The MICO platform is very poor at being correct about the number of animals when it does detect animals, and very likely to detect an incorrect number of animals. • There is some evidence to suggestion that MICO is more precise at counting animals in nighttime shots, at least for images containing a single animal - perhaps because distracting features such as clouds, bushes and shadows are not visible, reducing false positives. • Images with more than one species performed slightly better, perhaps because multiple MICO detectors contributed to the decision. • When testing images containing a single animal, the detectors for warthogs and ostriches performed especially well (precision of 75-84%) and the detector for wildebeest performed especially poorly (precision of 21%). These results may be partly explained by the prevalence of wildebeest and the rarity of ostriches in the dataset.
TP-506-01	**Test that species preferences match user behaviour***	• Simple queries sufficed to run the real-world tests, a machine learning approach was not needed and was not developed. • Species preferences as it came out of those queries matched user behaviour in all cases. • However, that means KPI values could not be calculated since there is no further benchmark to compare against.
TP-506-02	**Test that the subjects recommended match the preferred species***	• Simple queries sufficed to run the real-world tests, a machine learning approach was not needed and was not developed. • Subjects recommended as they came out of those queries contained the preferred species in all cases. • However, that means KPI values could not be calculated since there is no further benchmark to compare against
TP-506-03	**Test that different species preferences result in the correct changes to subject recommendations***	• Simple queries sufficed to run the real-world tests, a machine learning approach was not needed and was not developed. • Subjects recommended were all updated correctly when species preferences are updated and the recommendations recalculated. • However, that means KPI values could not be calculated since there is no further benchmark to compare against.

TP-506-04	**Real-world tests using recommender results**	• The user profile data enabled us to run the “Happy User Experiment”. This experiment told us that adding more interesting animal images actually deters users, contrary to our expectations. The finding is written up in more detail on the MICO blog: http://www.mico-project.eu/snapshot-serengeti-an-unexpected-discovery/
		• This experiment also opened up new avenues of research:
		  ○ http://bit.ly/blanks-poster
		  ○ http://bit.ly/blanks-papers
		• .. and made significant contributions to build infrastructure that Zooniverse can re-use in future:

		○ https://github.com/zooniverse/geordi ○ https://github.com/zooniverse/experiment-server ○ https://github.com/zooniverse/geordi-client

* : The titles of these Test Plan items were rather ambiguously worded in the test plan. They have been improved for readability, but the tests remain the same.

Detailed Test Reports

We ran our validation on a subset of TD-12. In total, we had about 25% of the entire dataset run through the extractor pipeline, or 250,000 images. Of this 25%, only 46,321 images had any usable result. No response was received for the other images.

Due to platform availability, we were only able to test an overall dataset of 50,270 images rather than the planned ~300,000. Nonetheless, we have been able to evaluate the performance, accuracy and usability of the platform.

Background of TE-202: Animal and Emptiness Detection

The Fraunhofer team developing the extractors decided that initially, the focus of development effort, and thus testing, would be on the following species:

- elephant
- ostrich
- warthog
- wildebeest
- buffalo

These species were selected as those where the team were most able to deliver a guess with acceptable accuracy using the planned detection approach. 18 other species were also trained, and may be further developed and tested later in the project.

Evaluation Approach

In order to assess the accuracy of each MICO platform determination, we need to know what is in each image. Fortunately, through human computation on Snapshot Serengeti, we have a “crowd answer” for every one of the 300,000 images in TD-12. As planned in “Dataset Normalization” in the Test Plan, we used aggregation techniques to generate an easy-to-use summary for each image, including what species it contained, how many animals were present, what time of day the image was taken, whether it was blank, and other data.

This was done using the script:
https://github.com/zooniverse/mongo-subject-extractor/blob/master/generate_detailed_consensus.rb

which generated a CSV which is available here:
https://github.com/zooniverse/mongo-subject-extractor/raw/master/consensus-detailed.csv.zip

and which looks like this (simplified for readability):

```
zooniverse_id,season,site_id,frames,time_of_day,classifications,crowd
_says,total_species,total_animals,crowd_says_if_multi,retire_reason
ASG000tu6x,5,U12,3,11:41,12,zebra,1,5,zebra,consensus
ASG000tu6y,5,U12,3,11:42,10,zebra,1,5,zebra,consensus
ASG000tu6z,5,U12,3,11:43,17,multi,2,6,wildebeest;zebra,consensus
```

This CSV was imported into the test harness described below, and used for evaluation of MICO results.

Test Sets Used

Under the test plan we had expected to use the TD-12, also known as Season 8, which contains 300,000 images. Unfortunately, as described above, we were only able to have a total of **50,270 images** analysed by the platform. For the purposes of this document, we refer to this set as the "entire dataset" - though in future we will expand testing with the full 300,000. Fortunately we were able to ensure good coverage for the five key species within this 50,270 images.

Entire Dataset

Each part of the dataset is given a test set name or filter name, and these are marked in brackets. The name for the whole set is **["entire_dataset"]**, which breaks down as follows:

- 36,734 blank images **["blank"]**
- 13,045 images containing a single species **["single_species"]**, consisting of:
    - 1,169 images containing only buffalo **["only_buffalo"]**
    - 1,190 images containing only elephant(s) **["only_elephant"]**
    - 1,1090 images containing only warthog(s) **["only_warthog"]**
    - 3,057 images containing only wildebeest* **["only_wildebeest"]**
    - 356 images containing only ostrich(es)** **["only_ostrich"]**
    - 6,183 images containing only a single species, not one of the above **["only_other"]**
- 491 images containing a mixture of species **=> "multi_species".** These can be filtered as follows (noting that some images occur in more than one group):
    - 18 images containing buffalo along with other species **["multi_including_buffalo"] *****
    - 7 images containing elephant(s) along with other species **["multi_including_elephant"] *****
    - 25 images containing warthog(s) along with other species **["multi_including_warthog"] *****
    - 323 images containing wildebeest along with other species **["multi_including_wildebeest"]**

- 1 image containing ostrich(es) along with other species **[“multi_including_buffalo”] *****
- 124 images containing none of the above species **[“multi_including_none_of_the_five”]**

* : This species had a lot more than the others because wildebeest are especially common in all Serengeti images
** : This species had a lot fewer than the others because ostrich are especially rare in all Serengeti images. 357 represents the total number of ostrich images available in the 300,000 original images.
*** : We have decided not to use these subsets in tests, as they have a sample size of less than 100 and therefore the results would not be useful or meaningful.

Complexity

To address the borderline case of simple versus complex, which is measured by the number of actual animals (regardless of species) present, we also broke down the sum of **single_species** and **multi_species** (in other words all non-blank images) as follows:

- 13,536 non-blank images **[“non_blank”]**, consisting of:
  - 6,172 images with only 1 animal present **[“one_animal”]**
  - 4,583 images with between 2 and 5 animals present **[“simple”]**
  - 2,781 images with 6 or more animals present **[“complex”]**

Animal Size

Given the fact that only 5 species were chosen with a variety of sizes between them (only buffalo and wildebeest share a similar size), and given that the detectors no longer deal in animal groups but rather in single species, we decided it was not necessary to test borderlines cases based on animal size. This will be addressed in future at the point where we support multiple species of each size.

Mixed Animal Types

To address the borderline case of single species images versus images containing a mixture of species, we used the **single_species** and **multi_species** groups as defined above (and their subgroups).

A note on animal types: The original test plan envisaged us that the MICO platform would recognize groups of species e.g. cat-like animals. Since this approach has been abandoned, we no longer worry about animal types and instead focus on the specific five species.

Day and Night

To test whether there is a difference in performance between daytime images and nighttime images, we created two small test sets of solely daytime and solely night time images. Unfortunately, these are quite small, because timestamps in the data prove to be unreliable, therefore we had to create these sets by visual inspection. The technical problem of how to accurately discern day and nighttime images without having to visually inspect every image is left as a possible future exercise.

The test sets here were:

- 368 images taken during daylight hours **[“daytime”]**
- 183 images taken during hours of darkness **[“nighttime”]**

Test Framework Used

We used the MICO Platform API developed by the team at Salzburg Research. See http://mico-project.bitbucket.org/api/ or document D6.2.2 for further details of custom animal detection and text analysis endpoints.

Using this API, the Zooniverse team was able to develop a test harness. The test harness is built into our MICO demo, the code for which is at:
https://github.com/zooniverse/mico-serengeti-demo

(The demo is currently deployed at:
http://mico-demo.snapshotserengeti.org/subjects)

The testing logic (which can be run as described below) had the following approach:

1. Run all images in entire_dataset through the API, with the platform set to animal detection mode
2. Keep polling the API until all images are processed (status=”finished”)
3. Store the MICO results in a database.
4. Calculate KPI test results and export to CSV:

RESULTS GENERATION SCRIPT - KPI Calculation - Pseudocode

```
for each defined test
  for each defined test set
    calculate the sample size
    for each subject
      compare each subject in this set against the subject content
CSV
      calculate whether true positive / false negative / etc
    next subject
    analyse total, calculate the KPI: precision, recall and F1 score
    generate a CSV row summarising results for this test set & test
  next test set
  generate summary CSV row for this test
next test
output all results to CSV
```

5. The CSV data (a sample of which is shown here, numbers rounded for readability) was then analysed to produce this report.

```
detector, filter,    sample_size,true_pos,true_neg,false_pos,false_neg,precision,recall,f1
emptiness,everything,50270,      16425,   10451,   3085,     20309,    0.84,     0.45,  0.58
emptiness,daytime,   368,        106,     76,      14,       172,      0.88,     0.38,  0.53
emptiness,nighttime, 183,        33,      76,      45,       29,       0.42,     0.53,  0.47
```

The results generation script is available on Github. See the demo project's README on how to use it.

TP-202-01 - Test emptiness detection across a season of subjects

For this test, we wanted to evaluate how the MICO platform performs at detecting whether or not an image contains animals. This corresponds to the Accuracy Definition for "Emptiness" under Methodology and Planning in the Test Plan.

Metrics for blank test sets

For testing the correct detection of an empty image, we defined a single test, **emptiness**, the metrics for which are as follows:

- Relevance is defined as "The image is blank"
- Selected is defined as "The image is identified as blank"
- This leads to the following definitions:
  - True positive (TP): Blank image correctly identified as blank
  - True negative (TN): Non-blank image correctly identified as containing animals
  - False negative (FN): Blank image incorrectly identified as containing animals
  - False positive (FP): Non-blank image incorrectly identified as blank
  - Precision: `TP / (TP+FP)`: The percentage of images identified as blank which do indeed contain no animals.
  - Recall: `TP / (TP+FN)`: The percentage of images which are actually blank that are correctly identified as containing no animals.
  - F1 score: `2*(Precision*Recall)/(Precision+Recall)`: overall measure of this test's accuracy, combining precision and recall

Metrics for test sets with no blank images

A number of the test sets, by definition, contained no blank images. Therefore for these tests, rather than omitting the test, we looked at how good the detector was at detecting the *absence* of empty images. In other words, we used an alternate definition of relevance in these tests:

- Relevance is defined as "The image contains one or more animals"
- Selected is defined as "The image is identified as containing no animals"
- This leads to the following definitions:
  - True positive: Non-blank image correctly identified as containing animals
  - True negative: Not applicable in this case, as there are no blank images.
  - False negative: Non-blank image incorrectly identified as containing no animals
  - False positive: Not applicable in this case, as there are no blank images.
  - Precision: Not applicable in this case, as there are no non-relevant images.
  - Recall: The percentage of images which are actually contain animals that are correctly identified as containing animals.

- F1 score: Not applicable in this case, as there is no figure for precision.

Test sets where this alternate set of metrics was used are marked with an asterisk in the results table below.

Results

The results were as follows. In this and all subsequent results tables, precision, recall and F1 scores of 75% or better are highlighted in green, and those same metrics are highlighted in red when they are equal to 25% or less.

Test Set used	*Sample Size*	*Relevant Images*	*True Pos*	*True Neg*	*False Pos*	*False Neg*	*Precision*	*Recall*	*F1 Score*
entire_dataset	50,270	36,734	16,425	10,451	3,085	20,309	84%	45%	58%
daytime	368	278	106	76	14	172	88%	38%	53%
nighttime	183	62	33	76	45	29	42%	53%	47%
blank	36,734	36,734	16,425	0	0	20,309	N/A	45%	N/A
non_blank	13,536	13,536*	10,451	0	0	3,085	N/A	77%	N/A
one_animal	6,172	6,172*	4,586	0	0	1,586	N/A	74%	N/A
simple	4,583	4,583*	3,674	0	0	909	N/A	80%	N/A
complex	2,781	2,781*	2,191	0	0	590	N/A	79%	N/A
single_species	13,045	13,045*	10,042	0	0	3,003	N/A	77%	N/A
only_buffalo	1,169	1,169*	913	0	0	256	N/A	78%	N/A
only_elephant	1,190	1,190*	893	0	0	297	N/A	75%	N/A
only_ostrich	356	356*	261	0	0	95	N/A	73%	N/A
only_warthog	1,090	1,090*	709	0	0	381	N/A	65%	N/A
only_wildebeest	3,057	3,057*	2,512	0	0	545	N/A	82%	N/A
only_other	6,183	6,183*	4,754	0	0	1,429	N/A	77%	N/A
multi_species	491	491*	409	0	0	82	N/A	83%	N/A
multi_including_ wildebeest	323	323*	267	0	0	56	N/A	N/A	N/A
multi_including_ none_of_the_five	124	124*	107	0	0	17	N/A	N/A	N/A

* : For these tests, the alternate definition of relevance was used, as described in “Metrics for test sets with no blank images” above.

Overall

Precision was high: When MICO determines an image to be blank, it has a high likelihood (84%) of being right.

Recall was low: MICO falsely classified 55% of blank images as containing animals. This is not a bad thing from Zooniverse's perspective, the tendency to overclassify is useful in ensuring we do not miss anything.

Day vs Night

MICO seems to be much more precise at determining blanks during the day than at night. At night, it is twice as likely to falsely consider a non-blank image to be blank.
The recall was similar between day and night - night time blank images are not noticeably harder to determine as blank as far as MICO is concerned

Simple vs Complex

The number of animals in an image did not make much difference in the ability of MICO to be sure that it wasn't blank. Images with more than one animal were about 5-6% more likely to be correctly identified as non-blank than those with one animal.

Species Mix

The number of different species in an image did not make much difference in the ability of MICO to be sure that it wasn't blank. Images with more than one species were about 6% more likely to be correctly identified as non-blank than those with one single species. This is probably because the results of multiple different species detectors contributed to the answer.

Specific Species

MICO's ability to confirm that images containing each of the different species was non-blank did not vary widely between species. Warthogs performed slightly worse, at 65% recall, and wildebeest slightly better, at 83%. The other species were all in the 70% range.

TP-202-02 - Test animal type detection across a season of subjects

For this test, we wanted to evaluate how the MICO platform performs at detecting the specific species of elephant, buffalo, wildebeest, warthog or ostrich. Or not an image contains animals. This corresponds to the Accuracy Definition for "Animal Type" under Methodology and Planning in the Test Plan. (Recall that the platform did not train animals in "type" groups as originally planned, so animal type simply maps to "species".

Metrics for test sets containing the desired species

For testing the correct detection of an empty image, we defined five tests, **animal_type_buffalo**, **animal_type_elephant**, **animal_type_warthog**, **animal_type_wildebeest**, and **animal_type_ostrich,** the metrics for which are as follows:

- Relevance is defined as "The image contains the specified species"
- Selected is defined as "The image is identified as containing the specified species"
- This leads to the following definitions, for a given species x:
    - True positive: Image containing species x correctly identified as containing species x
    - True negative: Image that does not contain species x correctly identified as not containing species x

- False negative: Image containing species x incorrectly identified as not containing species x
- False positive: Image that does not contain species x incorrectly identified as containing species x
- Precision: The percentage of images identified as containing species x which do indeed contain species x.
- Recall: The percentage of images which actually contain species x that are correctly identified as containing species x.
- F1 score: overall measure of this test's accuracy, combining precision and recall

Metrics for test sets which do not contain the desired species

A number of the test sets, by definition, did not contain the desired species for that test. Therefore for these tests, rather than omitting the test, we looked at how good the detector was at detecting the *absence* of species x. In other words, we used an alternate definition of relevance in these tests:

- Relevance is defined as "The image does not contain species x"
- Selected is defined as "The image is identified as not containing species x"
- This leads to the following definitions:
  - True positive: Image that does not contain species x correctly identified as not containing species x
  - True negative: Not applicable in this case, as there are no images containing species x.
  - False negative: Image that does not contain species x incorrectly identified as containing species x.
  - False positive: Not applicable in this case, as there are no images containing species x.
  - Precision: Not applicable in this case, as there are no non-relevant images.
  - Recall: The percentage of images which do not contain species x that are correctly identified as not containing species x.
  - F1 score: Not applicable in this case, as there is no figure for precision.

Test sets where this alternate set of metrics was used are marked with an asterisk in the results table below.

Results: Buffalo

The results for **animal_type_buffalo** were as follows.

Test Set used	*Sample Size*	*Relevant Images*	*True Pos*	*True Neg*	*False Pos*	*False Neg*	*Precision*	*Recall*	*F1 Score*
entire_dataset	50,270	1,187	387	41,179	7,904	800	5%	33%	8%
daytime	368	3	0	308	57	3	0%	0%	N/A
~~nighttime~~	183	0	N/A	N/A	N/A	N/A	N/A	N/A	N/A

blank	36,734	36,734*	32,091	0	0	4,643	N/A	87%	N/A
non_blank	13,536	1,187	387	9,088	3,261	800	11%	33%	16%
one_animal	6,172	464	146	4,280	1,428	318	9%	31%	14%
simple	4,583	415	138	2,965	1,203	277	10%	33%	16%
complex	2,781	308	103	1,843	630	205	14%	33%	20%
single_species	13,045	1,169	381	8,739	3,137	788	11%	33%	16%
only_buffalo	1,169	1,169	381	0	0	788	N/A	33%	N/A
only_elephant	1,190	1,190*	768	0	0	422	N/A	65%	N/A
only_ostrich	356	356*	288	0	0	68	N/A	81%	N/A
only_warthog	1,090	1,090*	819	0	0	271	N/A	75%	N/A
only_wildebeest	3,057	3,057*	2,111	0	0	946	N/A	69%	N/A
only_other	6,183	6,183*	4,753	0	0	1,430	N/A	77%	N/A
multi_species	491	18	6	349	124	12	5%	33%	8%
multi_including_ wildebeest	323	323*	237	0	0	86	N/A	73%	N/A
multi_including_ none_of_the_five	124	124*	90	0	0	34	N/A	73%	N/A

* : For these tests, the alternate definition of relevance was used, as described in “Metrics for test sets which do not contain the desired species” above.

The tests using the nighttime test sets were not available for this test, as there were no images containing buffalo in this test set.

Results: Elephants

The results for **animal_type_elephant** were as follows.

Test Set used	*Sample Size*	*Relevant Images*	*True Pos*	*True Neg*	*False Pos*	*False Neg*	*Precision*	*Recall*	*F1 Score*
entire_dataset	50,270	1,197	277	44,691	4,382	920	6%	23%	9%
daytime	368	8	1	326	34	7	3%	13%	5%
~~nighttime~~	183	0	N/A	N/A	N/A	N/A	N/A	N/A	N/A
blank	36,734	36,734*	34,048	0	0	2,686	N/A	93%	N/A
non_blank	13,536	1,197	277	10,643	1,696	920	14%	23%	17%
one_animal	6,172	610	130	4,810	752	480	15%	21%	17%
simple	4,583	473	133	3,497	613	340	18%	28%	22%

complex	2,781	114	14	2,336	331	100	4%	12%	6%
single_species	13,045	1,190	275	10,213	1,642	915	14%	23%	18%
only_buffalo	1,169	1,169*	963	0	0	206	N/A	82%	N/A
only_elephant	1,190	1,190	275	0	0	915	N/A	23%	N/A
only_ostrich	356	356*	335	0	0	21	N/A	94%	N/A
only_warthog	1,090	1,090*	957	0	0	133	N/A	88%	N/A
only_wildebeest	3,057	3,057*	2,603	0	0	454	N/A	85%	N/A
only_other	6,183	6,183*	5,355	0	0	828	N/A	87%	N/A
multi_species	491	7	2	430	54	5	4%	29%	6%
multi_including_ wildebeest	323	323*	281	0	0	42	N/A	87%	N/A
multi_including_ none_of_the_five	124	124*	117	0	0	7	N/A	94%	N/A

* : For these tests, the alternate definition of relevance was used, as described in “Metrics for test sets which do not contain the desired species” above.

The tests using the nighttime test sets were not available for this test, as there were no images containing elephants in this test set.

Results: Ostriches

The results for **animal_type_ostrich** were as follows.

Test Set used	*Sample Size*	*Relevant Images*	*True Pos*	*True Neg*	*False Pos*	*False Neg*	*Precision*	*Recall*	*F1 Score*
entire_dataset	50,270	357	219	29,181	20,732	138	1%	61%	2%
daytime	368	2	2	192	174	0	1%	100%	2%
~~nighttime~~	183	0	N/A	N/A	N/A	N/A	N/A	N/A	N/A
blank	36,734	36,734*	22,985	0	0	13,749	N/A	63%	N/A
non_blank	13,536	357	219	6,196	6,983	138	3%	61%	6%
one_animal	6,172	287	176	2,991	2,894	111	6%	61%	10%
simple	4,583	67	41	2,033	2,483	26	2%	61%	3%
complex	2,781	3	2	1,172	1,606	1	0%	67%	0%
single_species	13,045	356	219	6,018	6,671	137	3%	62%	6%
only_buffalo	1,169	1,169*	631	0	0	538	N/A	54%	N/A
only_elephant	1,190	1,190*	720	0	0	470	N/A	61%	N/A

only_ostrich	356	356	219	0	0	137	N/A	62%	N/A
only_warthog	1,090	1,090*	714	0	0	376	N/A	66%	N/A
only_wildebeest	3,057	3,057*	1,353	0	0	1,704	N/A	44%	N/A
only_other	6,183	6,183*	2,600	0	0	3,583	N/A	42%	N/A
multi_species	491	1	0	178	312	1	0%	0%	N/A
multi_including_ wildebeest	323	323*	116	0	0	207	N/A	36%	N/A
multi_including_ none_of_the_five	124	124*	43	0	0	81	N/A	35%	N/A

* : For these tests, the alternate definition of relevance was used, as described in “Metrics for test sets which do not contain the desired species” above.

The tests using the nighttime test sets were not available for this test, as there were no images containing ostriches in this test set.

Results: Warthogs

The results for **animal_type_warthog** were as follows.

Test Set used	*Sample Size*	*Relevant Images*	*True Pos*	*True Neg*	*False Pos*	*False Neg*	*Precision*	*Recall*	*F1 Score*
entire_dataset	50,270	1,115	432	35,643	13,512	683	3%	39%	6%
daytime	368	9	3	250	109	6	3%	33%	5%
~~nighttime~~	183	0	N/A	N/A	N/A	N/A	N/A	N/A	N/A
blank	36,734	36,734*	27,977	0	0	8,757	N/A	76%	N/A
non_blank	13,536	1,115	432	7,666	4,755	683	8%	39%	14%
one_animal	6,172	836	344	3,451	1,885	492	15%	41%	22%
simple	4,583	257	79	2,496	1,830	178	4%	31%	7%
complex	2,781	22	9	1,719	1,040	13	1%	41%	2%
single_species	13,045	1,090	422	7,384	4,571	668	8%	39%	14%
only_buffalo	1,169	1,169*	668	0	0	501	N/A	57%	N/A
only_elephant	1,190	1,190*	707	0	0	483	N/A	59%	N/A
only_ostrich	356	356*	261	0	0	95	N/A	73%	N/A
only_warthog	1,090	1,090	422	0	0	668	N/A	39%	N/A
only_wildebeest	3,057	3,057*	1,756	0	0	1,301	N/A	57%	N/A
only_other	6,183	6,183*	3,992	0	0	2,191	N/A	65%	N/A

multi_species	491	25	10	282	184	15	5%	40%	9%
multi_including_ wildebeest	323	319*	187	2	2	132	99%	59%	74%
multi_including_ none_of_the_five	124	124*	77	0	0	47	N/A	62%	N/A

* : For these tests, the alternate definition of relevance was used, as described in “Metrics for test sets which do not contain the desired species” above.

The tests using the nighttime test sets were not available for this test, as there were no images containing warthogs in this test set.

Results: Wildebeest

The results for **animal_type_wildebeest** were as follows.

Test Set used	*Sample Size*	*Relevant Images*	*True Pos*	*True Neg*	*False Pos*	*False Neg*	*Precision*	*Recall*	*F1 Score*
entire_dataset	50,270	3,380	1,399	39,569	7,321	1,981	16%	41%	23%
daytime	368	25	8	281	62	17	11%	32%	17%
~~nighttime~~	183	0	N/A	N/A	N/A	N/A	N/A	N/A	N/A
blank	36,734	36,734*	32,306	0	0	4,428	N/A	88%	N/A
non_blank	13,536	3,380	1,399	7,263	2,893	1,981	33%	41%	36%
one_animal	6,172	602	198	4,108	1,462	404	12%	33%	18%
simple	4,583	1,061	488	2,409	1,113	573	30%	46%	37%
complex	2,781	1,717	713	746	318	1,004	69%	42%	52%
single_species	13,045	3,057	1,261	7,152	2,836	1,796	31%	41%	35%
only_buffalo	1,169	1,169*	817	0	0	352	N/A	70%	N/A
only_elephant	1,190	1,190*	890	0	0	300	N/A	75%	N/A
only_ostrich	356	356*	316	0	0	40	N/A	89%	N/A
only_warthog	1,090	1,090*	868	0	0	222	N/A	80%	N/A
only_wildebeest	3,057	3,057	1,261	0	0	1,796	N/A	41%	N/A
only_other	6,183	6,183*	4,261	0	0	1,922	N/A	69%	N/A
multi_species	491	323	138	111	57	185	71%	43%	53%
multi_including_ wildebeest	323	323	138	0	0	185	N/A	43%	N/A

multi_including_ none_of_the_five	124	124*	83	0	0	41	N/A	67%	N/A

* : For these tests, the alternate definition of relevance was used, as described in “Metrics for test sets which do not contain the desired species” above.

The tests using the nighttime test sets were not available for this test, as there were no images containing wildebeest in this test set.

Results: Summary

The results for **entire_dataset**, across all five tests were as follows:

Test	*Sample Size*	*Relevant Images*	*True Pos*	*True Neg*	*False Pos*	*False Neg*	*Precision*	*Recall*	*F1 Score*
animal_type_ buffalo	50,270	1,187	387	41,179	7,904	800	5%	33%	8%
animal_type_ elephant	50,270	1,197	277	44,691	4,382	920	6%	23%	9%
animal_type_ ostrich	50,270	357	219	29,181	20,732	138	1%	61%	2%
animal_type_ warthog	50,270	1,115	432	35,643	13,512	683	3%	39%	6%
animal_type_ wildebeest	50,270	3,380	1,399	39,569	7,321	1,981	16%	41%	23%
total	50,270	7,236	2,714	190,263	53,851	4,522	5%	38%	9%
average per species							6%	39%	10%

Overall

Overall, the precision was low - 6% or less. This means that the platform has a tendency to overclassify, and an extremely high chance (94% or more) of being incorrect (i.e. the species is not present) when it reports the presence of one of the five target species in a given image. As such, the platform is not yet useful as a means to pre-determine which species is present. We recognise that emptiness detection was the primary focus of the detectors at this stage, so this is not unexpected.
Overall, precision for wildebeest was about 10% higher. Still low, but considerably better than the other species. Whether this is in part due to the high prevalence of wildebeest in Serengeti images is unclear.

Recall - the ability of the platform to correctly recognize the presence of a species when it is present and not miss any - was generally better - varying between 23% (elephants) and 61% (ostriches). This level of performance is moderate, and in the case of ostriches, quite good. However we have observed that the platform identifies the presence of ostriches in the vast majority of images, so this, combined with the low number of ostriches in our dataset, may simply be a lucky “scattergun” success.

Day vs Night

None of the target species were present in our night time test set, therefore we are unable to say whether daylight makes species identification easier.

Simple vs Complex

There was in general a better precision and recall for species identification in complex images (those with more than 5 animals) than in simple ones (5 animals or fewer). However, buffalo gave identical recall for both simple and complex images.
Also worthy of note is the fact that for wildebeest, that precision (likelihood of being correct about the species being present) was much higher, and quite good, in complex images - 69% - than in simple images, where precision was poor - 30%. This means the wildebeest detector is more likely to be correct when it does report a buffalo - but, similarly to ostriches, this is probably explained by the scattergun theory - in this case because there *are* a very high number of buffalo in Serengeti images, therefore the numerous reports of buffalo in images are on average more likely to be correct.

Species Mix

In general precision and recall were higher for multi species images than single species images. This is again probably because multiple detectors contributed to the decision in those cases. Also, given that this is less true for ostriches, and more true for wildebeest, it is again an unreliable conclusion that is likely influenced by the prevalence of each species in the test data.

Specific Species

As mentioned above in “Overall”, precision was generally very poor - though slightly better for those species that are more commonly found. Recall was moderate, and heavily improved by the rarity of a given species. In short, we should be careful about drawing conclusions about the accuracy for specific species in these unequal test sets.

TP-202-03 - Test animal counting across a season of subjects

For this test, we wanted to evaluate how the MICO platform performs at detecting the correct number of animals. This corresponds to the Accuracy Definition for “Animal Count” under Methodology and Planning in the Test Plan.

Metrics for test sets with a mix of animal counts

For testing the correct detection of a specific animal count, we defined ten different tests, **animal_count_1** to **animal_count_10**, each corresponding to a trying to detect a specific number of animals. In each test, we did not have a tolerance threshold. In other words, when

testing for an animal count of 6 (**animal_count_6**) then any number other than 6 is counted as a fail, even 5 or 7.

For a given test **animal_count_x**, the metrics are as follows

- Relevance is defined as “The image contains exactly x animals”
- Selected is defined as “The image is identified as containing exactly x animals” (i.e. the detector detects x regions)
- This leads to the following definitions:
    - True positive: Image with x animals correctly identified as having x animals
    - True negative: Image with a number of animals other than x correctly identified as having a number of animals other than x.
    - False negative: Image with x animals incorrectly identified as having a number of animals other than x.
    - False positive: Image with a number of animals other than x incorrectly identified as having x animals
    - Precision: The percentage of images identified as having x animals which do indeed contain x animals.
    - Recall: The percentage of images which actually contain x animals that are correctly identified as containing x animals.
    - F1 score: overall measure of this test’s accuracy, combining precision and recall

Metrics for test sets where the desired count is impossible

A number of the test sets, by definition, do not contain the tested for number of animals. (For example, blank or multi_species cannot contain 1 animal. Therefore for these tests, rather than omitting the test, we looked at how good the detector was at detecting that the number of animals was *not* equal to the test value. In other words, we used an alternate definition of relevance in these tests, for a given test **animal_count_x**:

- Relevance is defined as “The image contains a number of animals other than x”
- Selected is defined as “The image is identified as containing a number of animals other than x”
- This leads to the following definitions:
    - True positive: Image with some number of animals other than x correctly identified as having some number of animals other than x
    - True negative: Not applicable in this case, as there are no images containing x animals.
    - False negative: Image with some number of animals other than x incorrectly identified as having a x animals.
    - False positive: Not applicable in this case, as there are no images containing x animals.
    - Precision: Not applicable in this case, as there are no non-relevant images.
    - Recall: The percentage of images which do not contain x animals that are correctly identified as containing some other number of animals than x.

- F1 score: Not applicable in this case, as there is no figure for precision.

Test sets where this alternate set of metrics was used are marked with an asterisk in the results table below.

Results: 1 animal

The results for **animal_count_1** were as follows:

Test Set used	*Sample Size*	*Relevant Images*	*True Pos*	*True Neg*	*False Pos*	*False Neg*	*Precision*	*Recall*	*F1 Score*
entire_dataset	50,270	6,172	1,188	34,776	9,322	4,984	11%	19%	14%
daytime	368	34	10	272	62	24	14%	29%	19%
nighttime	183	105	13	65	13	92	50%	12%	20%
blank	36,734	36,734*	28,727	0	0	8,007	N/A	78%	N/A
non_blank	13,536	6,172	1,188	6,049	1,315	4,984	47%	19%	27%
one_animal	6,172	6,172	1,188	0	0	4,984	N/A	19%	N/A
simple	4,583	4,583*	3,756	0	0	827	N/A	82%	N/A
complex	2,781	2,781*	2,293	0	0	488	N/A	82%	N/A
single_species	13,045	6,172	1,188	5,642	1,231	4,984	49%	19%	28%
only_buffalo	1,169	464	101	561	144	363	41%	22%	28%
only_elephant	1,190	610	146	466	114	464	56%	24%	34%
only_ostrich	356	287	76	54	15	211	84%	26%	40%
only_warthog	1,090	836	160	202	52	676	75%	19%	31%
only_wildebeest	3,057	602	108	2,054	401	494	21%	18%	19%
only_other	6,183	3,373	597	2,305	505	2,776	54%	18%	27%
multi_species	491	491*	407	0	0	84	N/A	84%	N/A
multi_including_ wildebeest	323	323*	272	0	0	51	N/A	81%	N/A
multi_including_ none_of_the_five	124	124*	100	0	0	24	N/A	84%	N/A

* : For these tests, the alternate definition of relevance was used, as described in “Metrics for test sets where the desired count is impossible” above.

Results: 2 animals

The results for **animal_count_2** were as follows:

Test Set used	*Sample Size*	*Relevant Images*	*True Pos*	*True Neg*	*False Pos*	*False Neg*	*Precision*	*Recall*	*F1 Score*
entire_dataset	50,270	2,109	285	41,942	6,219	1,824	4%	14%	7%
daytime	368	12	1	295	61	11	2%	8%	3%
nighttime	183	9	0	158	16	9	0%	0%	N/A
blank	36,734	36,734*	32,183	0	0	4,551	N/A	88%	N/A
non_blank	13,536	2,109	285	9,759	1,668	1,824	15%	14%	14%
one_animal	6,172	6,172*	5,284	0	0	888	N/A	86%	N/A
simple	4,583	2,109	285	2,127	347	1,824	45%	14%	21%
complex	2,781	2,781*	2,348	0	0	433	N/A	84%	N/A
single_species	13,045	2,031	279	9,403	1,611	1,752	15%	14%	14%
only_buffalo	1,169	195	26	821	153	169	15%	13%	14%
only_elephant	1,190	210	33	854	126	177	21%	16%	18%
only_ostrich	356	42	6	252	62	36	9%	14%	11%
only_warthog	1,090	162	16	789	139	146	10%	10%	10%
only_wildebeest	3,057	333	48	2,296	428	285	10%	14%	12%
only_other	6,183	1,089	150	4,391	703	939	18%	14%	15%
multi_species	491	78	6	356	57	72	10%	8%	9%
multi_including_ wildebeest	323	12	1	275	36	11	3%	8%	4%
multi_including_ none_of_the_five	124	49	2	57	18	47	10%	4%	6%

* : For these tests, the alternate definition of relevance was used, as described in “Metrics for test sets where the desired count is impossible” above.

Results: 3 animals

The results for **animal_count_3** were as follows:

Test Set used	*Sample Size*	*Relevant Images*	*True Pos*	*True Neg*	*False Pos*	*False Neg*	*Precision*	*Recall*	*F1 Score*
entire_dataset	50,270	1,232	124	45,090	3,948	1,108	3%	10%	5%
daytime	368	11	1	318	39	10	3%	9%	4%
nighttime	183	2	0	174	7	2	0%	0%	N/A
blank	36,734	36,734*	34,041	0	0	2,693	N/A	93%	N/A

non_blank	13,536	1,232	124	11,049	1,255	1,108	9%	10%	9%
one_animal	6,172	6,172*	5,552	0	0	620	N/A	90%	N/A
simple	4,583	1,232	124	3,007	344	1,108	26%	10%	15%
complex	2,781	2,781*	2,490	0	0	291	N/A	90%	N/A
single_species	13,045	1,190	116	10,648	1,207	1,074	9%	10%	9%
only_buffalo	1,169	108	6	940	121	102	5%	6%	5%
only_elephant	1,190	125	16	951	114	109	12%	13%	13%
only_ostrich	356	15	0	305	36	15	0%	0%	N/A
only_warthog	1,090	69	4	923	98	65	4%	6%	5%
only_wildebeest	3,057	303	31	2,476	278	272	10%	10%	10%
only_other	6,183	570	59	5,053	560	511	10%	10%	10%
multi_species	491	42	8	401	48	34	14%	19%	16%
multi_including_ wildebeest	323	20	4	277	26	16	13%	20%	16%
multi_including_ none_of_the_five	124	22	4	86	16	18	20%	18%	19%

* : For these tests, the alternate definition of relevance was used, as described in “Metrics for test sets where the desired count is impossible” above.

Results: 4 animals

The results for **animal_count_4** were as follows:

Test Set used	*Sample Size*	*Relevant Images*	*True Pos*	*True Neg*	*False Pos*	*False Neg*	*Precision*	*Recall*	*F1 Score*
entire_dataset	50,270	720	72	46,928	2,622	648	3%	10%	4%
daytime	368	7	0	338	23	7	0%	0%	N/A
nighttime	183	2	0	170	11	2	0%	0%	N/A
blank	36,734	36,734*	35,124	0	0	1,610	N/A	96%	N/A
non_blank	13,536	720	72	11,804	1,012	648	7%	10%	8%
one_animal	6,172	6,172*	5,711	0	0	461	N/A	93%	N/A
simple	4,583	720	72	3,533	330	648	18%	10%	13%
complex	2,781	2,781*	2,560	0	0	221	N/A	92%	N/A
single_species	13,045	674	68	11,386	985	606	6%	10%	8%
only_buffalo	1,169	66	4	1,011	92	62	4%	6%	5%

only_elephant	1,190	76	8	1,026	88	68	8%	11%	9%
only_ostrich	356	3	2	334	19	1	10%	67%	17%
only_warthog	1,090	13	1	1,005	72	12	1%	8%	2%
only_wildebeest	3,057	178	18	2,623	256	160	7%	10%	8%
only_other	6,183	338	35	5,387	458	303	7%	10%	8%
multi_species	491	46	4	418	27	42	13%	9%	10%
multi_including_ wildebeest	323	26	3	275	22	23	12%	12%	12%
multi_including_ none_of_the_five	124	16	1	105	3	15	25%	6%	10%

* : For these tests, the alternate definition of relevance was used, as described in “Metrics for test sets where the desired count is impossible” above.

Results: 5 animals

The results for **animal_count_5** were as follows:

Test Set used	*Sample Size*	*Relevant Images*	*True Pos*	*True Neg*	*False Pos*	*False Neg*	*Precision*	*Recall*	*F1 Score*
entire_dataset	50,270	522	36	47,859	1,889	486	2%	7%	3%
daytime	368	8	0	347	13	8	0%	0%	N/A
nighttime	183	1	0	173	9	1	0%	0%	N/A
blank	36,734	36,734*	35,660	0	0	1,074	N/A	97%	N/A
non_blank	13,536	522	36	12,199	815	486	4%	7%	5%
one_animal	6,172	6,172*	5,826	0	0	346	N/A	94%	N/A
simple	4,583	522	36	3,769	292	486	11%	7%	8%
complex	2,781	2,781*	2,604	0	0	177	N/A	94%	N/A
single_species	13,045	496	35	11,767	782	461	4%	7%	5%
only_buffalo	1,169	36	4	1,064	69	32	5%	11%	7%
only_elephant	1,190	58	5	1,081	51	53	9%	9%	9%
only_ostrich	356	6	2	332	18	4	10%	33%	15%
only_warthog	1,090	3	0	1,048	39	3	0%	0%	N/A
only_wildebeest	3,057	172	11	2,666	219	161	5%	6%	5%
only_other	6,183	221	13	5,576	386	208	3%	6%	4%
multi_species	491	26	1	432	33	25	3%	4%	3%

multi_including_ wildebeest	323	17	1	282	24	16	4%	6%	5%
multi_including_ none_of_the_five	124	8	0	107	9	8	0%	0%	N/A

* : For these tests, the alternate definition of relevance was used, as described in “Metrics for test sets where the desired count is impossible” above.

Results: 6 animals

The results for **animal_count_6** were as follows:

Test Set used	*Sample Size*	*Relevant Images*	*True Pos*	*True Neg*	*False Pos*	*False Neg*	*Precision*	*Recall*	*F1 Score*
entire_dataset	50,270	400	22	48,524	1,346	378	2%	6%	2%
daytime	368	2	0	353	13	2	0%	0%	N/A
~~nighttime~~	183	0	N/A	N/A	N/A	N/A	N/A	N/A	N/A
blank	36,734	36,734*	36,010	0	0	724	N/A	98%	N/A
non_blank	13,536	400	22	12,514	622	378	3%	6%	4%
one_animal	6,172	6,172*	5,904	0	0	268	N/A	96%	N/A
simple	4,583	4,583*	4,347	0	0	236	N/A	95%	N/A
complex	2,781	400	22	2,263	118	378	16%	6%	8%
single_species	13,045	362	19	12,093	590	343	3%	5%	4%
only_buffalo	1,169	37	1	1,078	54	36	2%	3%	2%
only_elephant	1,190	37	1	1,090	63	36	2%	3%	2%
only_ostrich	356	3	0	344	9	3	0%	0%	N/A
only_warthog	1,090	7	1	1,041	42	6	2%	14%	4%
only_wildebeest	3,057	144	11	2,764	149	133	7%	8%	7%
only_other	6,183	134	5	5,776	273	129	2%	4%	2%
multi_species	491	38	3	421	32	35	9%	8%	8%
multi_including_ wildebeest	323	18	3	281	24	15	11%	17%	13%
multi_including_ none_of_the_five	124	14	0	103	7	14	0%	0%	N/A

* : For these tests, the alternate definition of relevance was used, as described in “Metrics for test sets where the desired count is impossible” above.

The test using the nighttime test set was not available for this test, as there were no nighttime images containing 6 animals.

Results: 7 animals

The results for **animal_count_7** were as follows:

Test Set used	*Sample Size*	*Relevant Images*	*True Pos*	*True Neg*	*False Pos*	*False Neg*	*Precision*	*Recall*	*F1 Score*
entire_dataset	50,270	307	18	48,906	1,057	289	2%	6%	3%
daytime	368	3	0	359	6	3	0%	0%	N/A
nighttime	183	2	0	172	9	2	0%	0%	N/A
blank	36,734	36,734*	36,188	0	0	546	N/A	99%	N/A
non_blank	13,536	307	18	12,718	511	289	3%	6%	4%
one_animal	6,172	6,172*	5,965	0	0	207	N/A	97%	N/A
simple	4,583	4,583*	4,389	0	0	194	N/A	96%	N/A
complex	2,781	307	18	2,364	110	289	14%	6%	8%
single_species	13,045	277	13	12,276	492	264	3%	5%	3%
only_buffalo	1,169	41	1	1,087	41	40	2%	2%	2%
only_elephant	1,190	31	0	1,124	35	31	0%	0%	N/A
~~only_ostrich~~	356	0	N/A	N/A	N/A	N/A	N/A	N/A	N/A
~~only_warthog~~	1,090	0	N/A	N/A	N/A	N/A	N/A	N/A	N/A
only_wildebeest	3,057	98	11	2,807	152	87	7%	11%	8%
only_other	6,183	107	1	5,850	226	106	0%	1%	1%
multi_species	491	30	5	442	19	25	21%	17%	19%
multi_including_ wildebeest	323	26	5	287	10	21	33%	19%	24%
multi_including_ none_of_the_five	124	3	0	115	6	3	0%	0%	N/A

* : For these tests, the alternate definition of relevance was used, as described in “Metrics for test sets where the desired count is impossible” above.

The tests using the only_ostrich and only_warthog test sets were not available for this test, as there were no images containing 7 animals in these test sets.

Results: 8 animals

The results for **animal_count_8** were as follows:

Test Set used	*Sample Size*	*Relevant Images*	*True Pos*	*True Neg*	*False Pos*	*False Neg*	*Precision*	*Recall*	*F1 Score*
entire_dataset	50,270	245	2	49,209	816	243	0%	1%	0%
daytime	368	1	0	365	2	1	0%	0%	N/A
~~nighttime~~	183	0	N/A	N/A	N/A	N/A	N/A	N/A	N/A
blank	36,734	36,734*	36,354	0	0	380	N/A	99%	N/A
non_blank	13,536	245	2	12,855	436	243	0%	1%	1%
one_animal	6,172	6,172*	6,007	0	0	165	N/A	97%	N/A
simple	4,583	4,583*	4,408	0	0	175	N/A	96%	N/A
complex	2,781	245	2	2,440	96	243	2%	1%	1%
single_species	13,045	225	1	12,405	415	224	0%	0%	0%
only_buffalo	1,169	28	0	1,119	22	28	0%	0%	N/A
only_elephant	1,190	13	0	1,157	20	13	0%	0%	N/A
~~only_ostrich~~	356	0	N/A	N/A	N/A	N/A	N/A	N/A	N/A
~~only_warthog~~	1,090	0	N/A	N/A	N/A	N/A	N/A	N/A	N/A
only_wildebeest	3,057	103	1	2,820	134	102	1%	1%	1%
only_other	6,183	81	0	5,881	221	81	0%	0%	N/A
multi_species	491	20	1	450	21	19	5%	5%	5%
multi_including_ wildebeest	323	17	1	289	17	16	6%	6%	6%
multi_including_ none_of_the_five	124	1	0	120	3	1	0%	0%	N/A

* : For these tests, the alternate definition of relevance was used, as described in “Metrics for test sets where the desired count is impossible” above.

The tests using the nighttime, only_ostrich and only_warthog test sets were not available for this test, as there were no images containing 8 animals in these test sets.

Results: 9 animals

The results for **animal_count_9** were as follows:

Test Set used	*Sample Size*	*Relevant Images*	*True Pos*	*True Neg*	*False Pos*	*False Neg*	*Precision*	*Recall*	*F1 Score*
entire_dataset	50,270	158	5	49,514	598	153	1%	3%	1%
~~daytime~~	368	0	N/A	N/A	N/A	N/A	N/A	N/A	N/A
~~nighttime~~	183	0	N/A	N/A	N/A	N/A	N/A	N/A	N/A
blank	36,734	36,734*	36,460	0	0	274	N/A	99%	N/A
non_blank	13,536	158	5	13,054	324	153	2%	3%	2%
one_animal	6,172	6,172*	6,044	0	0	128	N/A	98%	N/A
simple	4,583	4,583*	4,454	0	0	129	N/A	97%	N/A
complex	2,781	158	5	2,556	67	153	7%	3%	4%
single_species	13,045	138	4	12,597	310	134	1%	3%	2%
only_buffalo	1,169	20	1	1,129	20	19	5%	5%	5%
only_elephant	1,190	17	0	1,147	26	17	0%	0%	N/A
~~only_ostrich~~	356	0	N/A	N/A	N/A	N/A	N/A	N/A	N/A
~~only_warthog~~	1,090	0	N/A	N/A	N/A	N/A	N/A	N/A	N/A
only_wildebeest	3,057	51	2	2,918	88	49	2%	4%	3%
only_other	6,183	50	1	5,975	158	49	1%	2%	1%
multi_species	491	20	1	457	14	19	7%	5%	6%
multi_including_ wildebeest	323	12	1	301	10	11	9%	8%	9%
multi_including_ none_of_the_five	124	2	0	120	2	2	0%	0%	N/A

* : For these tests, the alternate definition of relevance was used, as described in “Metrics for test sets where the desired count is impossible” above.

The tests using the daytime, nighttime, only_ostrich and only_warthog test sets were not available for this test, as there were no images containing 9 animals in these test sets.

Results: 10 animals

The results for **animal_count_10** were as follows:

Test Set used	*Sample Size*	*Relevant Images*	*True Pos*	*True Neg*	*False Pos*	*False Neg*	*Precision*	*Recall*	*F1 Score*
entire_dataset	50,270	165	3	49,664	441	162	1%	2%	1%
daytime	368	1	0	365	2	1	0%	0%	N/A
~~nighttime~~	183	0	N/A	N/A	N/A	N/A	N/A	N/A	N/A

blank	36,734	36,734	36,544	0	0	190	N/A	99%	N/A
non_blank	13,536	165	3	13,120	251	162	1%	2%	1%
one_animal	6,172	6,172	6,063	0	0	109	N/A	98%	N/A
simple	4,583	4,583	4,489	0	0	94	N/A	98%	N/A
complex	2,781	165	3	2,568	48	162	6%	2%	3%
single_species	13,045	153	3	12,651	241	150	1%	2%	2%
only_buffalo	1,169	32	0	1,118	19	32	0%	0%	N/A
only_elephant	1,190	7	1	1,169	14	6	7%	14%	9%
~~only_ostrich~~	356	0	N/A	N/A	N/A	N/A	N/A	N/A	N/A
~~only_warthog~~	1,090	0	N/A	N/A	N/A	N/A	N/A	N/A	N/A
only_wildebeest	3,057	71	1	2,928	58	70	2%	1%	2%
only_other	6,183	43	1	6,003	137	42	1%	2%	1%
multi_species	491	12	0	469	10	12	0%	0%	N/A
multi_including_ wildebeest	323	10	0	303	10	10	0%	0%	N/A
multi_including_ none_of_the_five	124	2	0	122	0	2	N/A	0%	N/A

* : For these tests, the alternate definition of relevance was used, as described in “Metrics for test sets where the desired count is impossible” above.

The tests using the nighttime, only_ostrich and only_warthog test sets were not available for this test, as there were no images containing 10 animals in these test sets.

Results: Summary

The results for **entire_dataset**, across all ten tests were as follows:

Test	*Sample Size*	*Relevant Images*	*True Pos*	*True Neg*	*False Pos*	*False Neg*	*Precision*	*Recall*	*F1 Score*
animal_count_1	50,270	6,172	1,188	34,776	9,322	4,984	11%	19%	14%
animal_count_2	50,270	2,109	285	41,942	6,219	1,824	4%	14%	7%
animal_count_3	50,270	1,232	124	45,090	3,948	1,108	3%	10%	5%
animal_count_4	50,270	720	72	46,928	2,622	648	3%	10%	4%
animal_count_5	50,270	522	36	47,859	1,889	486	2%	7%	3%
animal_count_6	50,270	400	22	48,524	1,346	378	2%	6%	2%
animal_count_7	50,270	307	18	48,906	1,057	289	2%	6%	3%

animal_count_8	50,270	245	2	49,209	816	243	0%	1%	0%
animal_count_9	50,270	158	5	49,514	598	153	1%	3%	1%
animal_count_10	50,270	165	3	49,664	441	162	1%	2%	1%
total	50,270	12,030	1,755	462,412	28,258	10,275	6%	15%	8%
average per count							3%	8%	4%

Overall

Both precision and recall were uniformly very low. The MICO platform is very poor at being correct about the number of animals when it does detect animals, and very likely to detect an incorrect number of animals.
The only good results were obtained in those cases where the relevance definition was switched; MICO is extremely good at saying when the number animals present is NOT equal to a target - however, this is unremarkable, as it's very easy for any random guess at the number of animals to be wrong.
For this reason, these reversed tests under animal_count_x should probably be discarded as not useful. However at this stage they are left in the report for completeness.

Day vs Night

For those values of x where MICO was able to get the correct number of animals at all - 1, 2 and 3, it did seem that daytime images achieved a higher recall than nighttime ones, almost twice as much in some cases. In other words, MICO is better at being right on the number of animals, regardless of target, in the daytime. Performance is better for smaller values of n - especially 1, but even then, at recall of 29%, the recall is still poor.
The same effect seems to hold for precision at low values of x too, with a better precision during daytime than at night for 2 or 3 animals.

Interestingly, for 1 animal, the opposite seems to hold true, with a precision of 50% at night compared to only 14% in the day. One theory for this is that fewer "distracting features" such as clouds, bushes or shadows are available at night to be mistaken for animals, thus the false positives are low. It is unclear why this effect would not continue for precision with all values of x at night, however the number of relevant images for each value of x is so low that this could be a fluke. Further testing with a larger test set would be desirable.

For 4 animals or more, precision and recall were both 0 for the day/night test sets so no distinction can be made between night and day.

Simple vs Complex

As mentioned above under "Overall", the number of animals present doesn't make any noticeable difference to precision or recall. The scores remain almost identical for all x values - always below 10% and usually around 3%. Where the relevance definition was inverted, the

precisions and recalls are inverted too (90% and 97%). Again, this is unremarkable and these reversed tests should probably be discarded.

Species Mix

The number of different species in an image did not make much difference in the ability of MICO to count the number of animals correctly. Images with more than one species were a generally more likely to be counted correctly than those with one single species, by a factor of 3-10%, though there are exceptions to this. This is probably because the results of multiple different species detectors contributed to the answer.

Specific Species

MICO's ability to correctly count the number of animals correctly did vary quite a lot between the 5 species, however the precision and recall were poor (10-15% or less) for almost all values of x for all 5 species. Wildebeest in general performed slightly better for both metrics, though this may be influenced by the very high number of wildebeest in Serengeti photos compared to other species (it is the most prevalent).

One exception is when determining whether an image contains exactly 1 animal - the extractors for warthogs and ostriches performed exceptionally well for this - with precision values of 75% and 84% respectively. It is unclear why these particular species with this particular x value would be better than others. Also for 1 animal the precision for wildebeest is especially low - 21% - meaning MICO is more likely to miscount the number of wildebeest in solo wildebeest pictures than for other species. Again the reason for this is unclear.

Overall Analysis of Platform for TP-202 (Animal Detection)

Accuracy

Best Precision

The top ten tests/test set combinations by precision were:

Test	Test Set	Sample size	Precision	Recall	F1 score
animal_type_warthog	multi_including_wildebeest	323	99%*	59%	74%
emptiness	daytime	368	88%	38%	53%
emptiness	entire_dataset	50,270	84%	45%	58%
animal_count_1	only_ostrich	356	84%	26%	40%
animal_count_1	only_warthog	1,090	75%	19%	31%
animal_type_wildebeest	multi_species	491	71%	43%	53%
animal_type_wildebeest	complex	2,781	69%	42%	52%
animal_count_1	only_elephant	1,190	56%	24%	34%

animal_count_1	only_other	6,183	54%	18%	27%
animal_count_1	nighttime	183	50%	12%	20%

* This test used an alternate relevancy definition and therefore we will disregard it for this purpose.

We can see that MICO is most precise when analysing emptiness, especially in the daytime, or when identifying a single wildebeest or the presence of wildebeest in multi-animal or multi-species images (which may related to their high prevalence).

Best Recall

The top ten test/test set combinations by recall (discarding tests that used an alternate relevancy definition) are:

Tested	Filter	Sample size	Precision	Recall	F1 score
animal_type_ostrich	daytime	368	1%	100%	2%
animal_count_4	only_ostrich	356	10%	67%	17%
animal_type_ostrich	complex	2,781	0%	67%	0%
animal_type_ostrich	single_species	13,045	3%	62%	6%
animal_type_ostrich	only_ostrich	356	N/A	62%	N/A
animal_type_ostrich	entire_dataset	50,270	1%	61%	2%
animal_type_ostrich	non_blank	13,536	3%	61%	6%
animal_type_ostrich	one_animal	6,172	6%	61%	10%
animal_type_ostrich	simple	4,583	2%	61%	3%
emptiness	nighttime	183	42%	53%	47%

We can see that MICO's recall is best when detecting species that are very rare, or on a test that has a small sample size. Many tests had higher recall scores, but were discarded due to having an alternate relevancy definition (this top ten actually spans the top-92 if we didn't discard tests).

Best F1 score

The top ten test/test set combinations by precision are:

Tested	Filter	Sample size	Precision	Recall	F1 score
animal_type_warthog	multi_including_wildebeest	323	99%	59%	74%*
emptiness	entire_dataset	50,270	84%	45%	58%
animal_type_ wildebeest	multi_species	491	71%	43%	53%
emptiness	daytime	368	88%	38%	53%
animal_type_ wildebeest	complex	2,781	69%	42%	52%
emptiness	nighttime	183	42%	53%	47%
animal_count_1	only_ostrich	356	84%	26%	40%
animal_type_ wildebeest	simple	4,583	30%	46%	37%
animal_type_ wildebeest	non_blank	13,536	33%	41%	36%
animal_type_ wildebeest	single_species	13,045	31%	41%	35%

* This test used an alternate relevancy definition and so will be ignored for this purpose.

Overall, looking at both precision and recall through the combined metric of F1 score, we can see the MICO platform is best at doing what it was designed to do best - determining the emptiness of an image. In addition, it seems to perform well with wildebeest (mainly in groups) and ostriches (mainly alone - both of these may simply reflect the high/low prevalence (respectively) of those species in the dataset.

Note that there is a rapid drop off in F1 score, plummeting to 35% by the end of the top ten. This tells us that MICO is good at only a few things, rather than many different things.

Worst Precision

The bottom five test/test set combinations by precision were:

Test	Test Set	Sample size	Precision	Recall	F1 score
animal_count_10	only_buffalo	1,169	0%	0%	N/A
animal_count_10	multi_species	491	0%	0%	N/A

animal_count_10	multi_including_wildebeest	323	0%	0%	N/A
animal_type_buffalo	daytime	368	0%	0%	N/A
animal_type_ostrich	multi_species	491	0%	0%	N/A

We can see that precision is worst when the specific number of animals, or specific species, is rare in the dataset.

Worst Recall

The bottom five test/test set combinations by recall were:

Test	Test Set	Sample size	Precision	Recall	F1 score
animal_count_10	multi_species	491	0%	0%	N/A
animal_count_10	multi_including_wildebeest	323	0%	0%	N/A
animal_count_10	multi_including_ none_of_the_five	124	N/A	0%	N/A
animal_type_buffalo	daytime	368	0%	0%	N/A
animal_type_ostrich	multi_species	491	0%	0%	N/A

We can see that recall (not missing relevant images) is worst when looking at images with mixed species or when looking for high animal counts. This could be because images with lots of animals often contain very small hard-to-identify animals in the distance or in overlapping groups. The poor recall with buffalo may be explained by their similarity to wildebeest.

Worst F1 score

The bottom five test/test set combinations by F1 score were:

Test	Test Set	Sample size	Precision	Recall	F1 score
animal_count_7	only_other	6,183	0%	1%	1%
animal_count_8	non_blank	13,536	0%	1%	1%
animal_count_8	entire_dataset	50,270	0%	1%	0%
animal_count_8	single_species	13,045	0%	0%	0%
animal_type_ostrich	complex	2,781	0%	67%	0%

Overall, looking at both precision and recall through the combined metric of F1 score, we can see that being accurate to specific count of animals present is a weakness of the platform, especially when that number is large. Similarly, when looking at images containing many animals, MICO performs worst with the rarest species - ostriches.

Latency

We measured the time it took from sending an image to the platform, until we had a final result back. We sent and timed a total of 1397 images. We found a mean time of 5.43 seconds, with a standard deviation of 9.75 seconds. The 90th-percentile was 5.90 seconds. Given that in a real world usage, Zooniverse would pre-process all images with MICO prior to the launch of a new season of images, Zooniverse is more interested in the overall throughput of the platform than the latency per image therefore we do not make a value judgement as to the

Throughput

The platform can cope with multiple parallel submissions, which means that in practice we can expect about to process about on average 0.71 images per second. This would mean that we could expect to process the entire TD-12 dataset (300,000 images) in about 5 days of non-stop processing time. Since the image extraction is a preprocessing step before we launch a project, and that phase takes time anyway, for the Zooniverse use case this would be perfectly acceptable.

Stability

In our testing, the platform was constantly crashing and out of commision. This meant that we struggled to get even 5% of our TD-12 test set processed for this report. This is a critical issue that needs to be addressed before we would be able to use the platform.

Modularity

The current version of the broker can only handle one active extraction pipeline. This means that to process both images and comments, we would need to work around this limitation by either switching between extractors automatically (which increases latency and probably removes parallelism which decreases throughput), or have to run two instances of the broker. Work to remove this limitation is underway.

Integration

We found the platform really easy to integrate. Integration for the demo application was very easy and done in about 100 lines of Ruby code. (See https://github.com/zooniverse/mico-api-client). The only real issue we have with the API the platform currently provides is that analysis cannot return a “failed” status and/or reason in the current version of the platform, which allows errors to go unnoticed.

Usefulness

The ability to get an 84% precise opinion upon whether an image is blank is **immediately useful** to Zooniverse. Our data scientist ran a simulation of how many classifications would be

needed to correctly classify all of the 300,000 images in Season 8 / TD-12 as blank or non-blank, and found that:

- Normally, without MICO, we would require at least 3 people to agree an image is blank before we can safely retire it and define it as blank (with a tiny error rate of only 0.18%)
- Adding MICO's determination into the mix, we can drop this down to just 2 users required where MICO thinks the image is blank (when MICO says it is non-blank, we still need 3 users).
- Without MICO, and using 3 people per image, we need 817,015 classifications to correctly classify all blank and non-blank images in TD-12.
- With MICO used as described above, we need only 702,404 classifications:
    - **Using the emptiness detection, MICO can save us over 115,000 classifications and allow us complete a season of data on Snapshot Serengeti in ⅞ of the time - which is of the order of several days to a week of volunteer time.**

Caveat: These figures are estimates, based on initial calculations and simulations, and have not been tested "in the wild".

Nonetheless, **this is an excellent and exciting prospect for Zooniverse and a clear positive outcome for the MICO project.**

Evaluation of Testing Approach for TE-202 (Animal detection)

In general, our testing strategy has been useful for giving an overview of the platform's ability, especially when looking at the accuracy across the entire dataset. However, some weaknesses were identified:

- The large variability in the chance that a given image will contain a certain species makes it much harder to trust the precision and recall values for detection of specific species. In future testing we will need to do more to normalize the number of each species present in all test data sets. For example, the high occurrence of wildebeest and the low number of ostriches have clearly biased those detectors' results for precision and recall respectively.
- The low number of images for day and night time sets has limited the usefulness of those tests. In future we hope to design a solution to properly determine the day-or-night status of all images in our test set, this will mean fewer tests having to be discarded due to not having enough occurrences of a particular number of animals or species in the day/night test sets.
- Similarly, having more processing time available on the platform will allow us to create much larger test sets for the 5 specific species. This too will increase the accuracy of species-specific tests. We may need to look for additional ostrich images in past seasons of Serengeti data outside of TD-12, since there are so few present in even the full 300,000 images.
- The decision to invert the relevancy definition in some cases to open up more possible test sets had some limited success in telling us more about the platform's capability, but

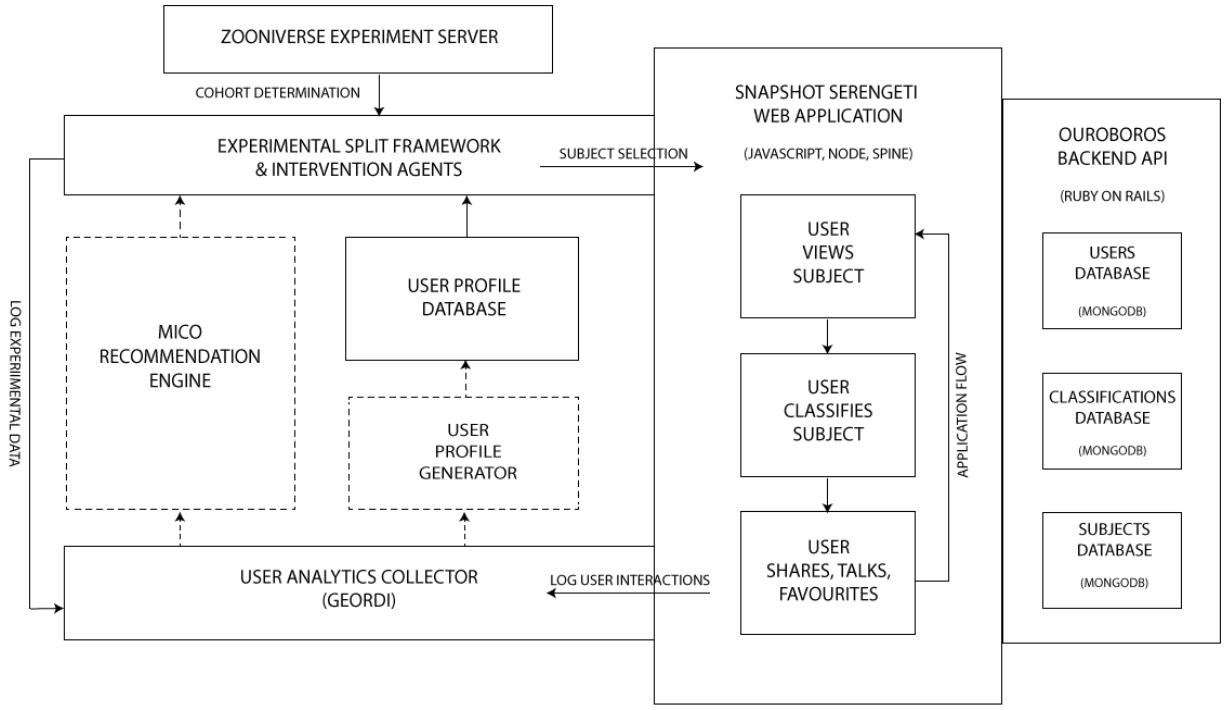
this approach needs more refinement as some of these inverted rows are misleading and show a high performance quality when that isn't really the case (e.g. confirming that an image doesn't have exactly 3 animals).

In future test cycles we hope to address many of these weaknesses.

Background and Context of TE-506: Cross modal content recommender

Some progress was made by Zaizi towards a Prediction-IO based machine learning solution for subject recommendation. Zooniverse made parallel efforts to build a simple subject recommendation system which suited our existing user base, using a flexible combination of MySQL queries and Python scripts, which would serve the same purpose.

This is marked as a dotted box called "User Profile Generator" in the architecture diagram shown below (which was included in the linked First Prototype document):



The original Test Plan for this work was written at a time when it was still expected that the Zaizi solution would become part of the MICO platform, so some of it is no longer relevant. However, the Zooniverse user profile generator/recommender system was found to be perfectly adequate for the needs of the Happy User Experiment.

What follows is an account of what was done to develop and functionally test each stage of the Zooniverse recommender system ("user profile generator"), which meets the functional capabilities for TE-506 of being able to recommend subjects for a user based on their behaviour and inferred preferences.

We are confident that the work done is sufficiently in line with the goals of WP5, and that it made more sense to keep the current test plan rather than abandon it and re-plan from scratch.

We concluded based on the results of TP-506-04 below that the theory of using user personalised subject selection based on “preferred” species was not particularly useful (given that the use of the recommended subjects damaged rather than improved participation), and the focus of MICO/Zooniverse work moved towards the use of animal detection and sentiment analysis/NER as cross media sources for recommendations, while the research angle moved towards investigation of the impact of blank subjects.

TP-506-01 - Test that species preferences match user behaviour

This test focussed on validating that a recommendation system trained upon user analytics data and species content data could correctly identify a user’s species preferences.

First, subject species content (TD-16) was calculated for all past Snapshot Serengeti users using a combination of MySQL queries and Python scripts [“DETERMINE SUBJECT CONTENT” above]

DETERMINE SUBJECT CONTENT - Pseudocode

```
for each subject
  combine all user classifications for this subject
  find the mode species (ie. that which the most users classified)
  store this as the dominant species for this subject
next subject
```

This was done by aggregating all user classifications for the subjects and taking the most commonly occurring answer, or “blank”, as the correct indication of subject content - as shown in the pseudocode above. Where more than one species was present (only 6% of images) we take the more numerous species.

Sample of TD-16 data

id	subjectID	species
335949	ASG0000017	blank
335950	ASG0000018	blank
335951	ASG0000019	elephant
335952	ASG000001a	elephant
335953	ASG000001b	leopard
335954	ASG000001c	blank
335955	ASG000001d	giraffe
335956	ASG000001e	blank
335957	ASG000001f	blank
335958	ASG000001g	blank
335959	ASG000001h	dikdik
335960	ASG000001i	blank
335961	ASG000001j	blank
335962	ASG000001k	gazellethomsons
335963	ASG000001l	blank
335964	ASG000001m	impala

Now that we have this data, we are then able to determine users' preferred species by looking at which subjects they prefer.
The general approach for generating TD-14 was as follows (again this was done using a combination of MySQL queries and Python scripts).

The procedure was

- Identify and tally indications of positive interest in a subject from the analytics data ["COLLECT SUBJECT INTEREST DATA" in diagram above]. We included the following user events:
    - User favourites the subject
    - User shares the subject via Facebook, pinterest or Twitter
    - User views the discussion page for a subject
    - User views the map for a subject

COLLECT SUBJECT INTEREST DATA - Pseudocode

```
for each user
  for each "positive interest" user analytics event
    increment interest counter for that subject for that user
  next analytics event
  store total interest by subject for each user
next user
```

- Convert each tallied indication of interest in a subject, to an indication of interest in the dominant species (or "blank") of that subject ["DETERMINE SPECIES INTEREST" in diagram above]. Each indication of interest is assigned a simple numerical score of 1.

DETERMINE SPECIES INTEREST - Pseudocode

```
for each user
  for each subject with positive interest
    determine which species is present (from TD-16)
    increment interest counter for that species for that user
  next subject
  store total "expressions of interest" per species for this user
next user
```

- Assign a score per user, per species, based on the sum of total expressions of interest in that species by that user ["GENERATE USER PROFILES" in diagram above]. So for example, if a user favourites an image of a zebra and shares two images containing lions, they would score 2.0 for lions and 1.0 for zebra. A higher score indicates a stronger interest in that species, and the two highest scoring species for a user can be deemed as that user's "favorite" species.

GENERATE USER PROFILES - Pseudocode

```
for each user
  for each species with positive interest
    add an entry in that user's profile that they like that species
    count number of expressions of interest for that species
    assign that number as a score to the user profile entry
  next species
next user
```

Sample of data from TD-14 user profile data

id	userID	score	scoreType	secondaryID
17611	998037	3.000	interestInSpecies	elephant
17609	997519	1.000	interestInSpecies	zebra
17610	997519	1.000	interestInSpecies	wildebeest
17605	993649	1.000	interestInSpecies	elephant
17606	993649	1.000	interestInSpecies	baboon
17607	993649	1.000	interestInSpecies	blank
17608	993649	2.000	interestInSpecies	zebra
17603	99354	1.000	interestInSpecies	wildebeest
17604	99354	2.000	interestInSpecies	blank
17597	988918	1.000	interestInSpecies	wildebeest
17598	988918	2.000	interestInSpecies	zebra
17599	988918	1.000	interestInSpecies	blank
17600	988918	1.000	interestInSpecies	gazellegrants
17601	988918	1.000	interestInSpecies	gazellethomsons
17602	988918	1.000	interestInSpecies	human
17596	988799	1.000	interestInSpecies	zebra
17595	986174	1.000	interestInSpecies	wildebeest

Testing approach

Since the recommendation system built here was a series of scripts and queries rather than a service, testing focussed on data quality - ensuring the data was correct and accurately representing user's species preferences. This was done as follows: We randomly selected a few users and inspected their user profile data (TD-14) to identify their two favourite species (those with the highest score for that user). We then randomly selected 5 subjects which those users had expressed positive interest in and confirmed that the subjects contained predominantly those two favorite species. This test was successful. This approach is however self-referential to the dataset, and no statistics were calculated on how strong the correlation between our chosen expressions of interest and actually liking that animal is.

The KPIs planned (precision, recall, F1-measure) were not tested since we are no longer in a comparison to external known good data scenario.

The "changed behaviour" borderline case was tested by modifying user subject positive interest tallies to favour subjects containing different species, and re-generating the user profile data accordingly, and user's favourite species were observed to have changed correctly.

TP-506-02 - Test that the subjects recommended match the preferred species

This test focussed on ensuring that the correct subjects would be recommended (in line with the calculated species preferences for each user) for a user once that user's species preferences were known.

Subject recommendation was performed as follows, using a combination of MySQL queries and Python scripts:

- A random set of 100 subjects was chosen for each species and "blank", using the TD-16 data. We ensured that these images did not contain other secondary species ["GENERATE SUBJECT SETS PER SPECIES" in diagram above].

GENERATE USER PROFILES - Pseudocode

```
for each species
  initialize subject set for this species
  while subject set contains < 100 items
    current subject = random subject
    while current subject does not contain this species
      pick another random subject
    end while
    add this subject to the subject set
  end while
next species
```

Sample of “SUBJECT SETS PER SPECIES” data

id	species	subjectIDs
139	gazelleGrants	ASG000dua0,ASG0011llk,ASG0002y3l,ASG0002hbw,ASG0002kdt,ASG0000283,ASG000…
140	gazelleThomsons	ASG000q46r,ASG0008l4l,ASG0002lg7,ASG0008lgm,ASG0002qyn,ASG0002rvr,ASG000…
141	genet	ASG00022xy,ASG000rtjl,ASG0000aho,ASG00016ly,ASG000ofkd,ASG0004bn9,ASG0008…
142	giraffe	ASG0002psj,ASG000bo9d,ASG000qin5,ASG0005qsl,ASG000qlj5,ASG000qpdh,ASG000…
143	guineaFowl	ASG0011ghv,ASG000qel5,ASG0003v8j,ASG0003ve5,ASG00001ap,ASG0006023,ASG00…
144	hare	ASG00070d8,ASG0000fpz,ASG0002ujq,ASG0004bvh,ASG000n0c9,ASG0000fqc,ASG00…
145	hartebeest	ASG0003xc2,ASG0003wxl,ASG0003xs1,ASG0003vvc,ASG0003vy0,ASG0003vu4,ASG00…
146	hippopotamus	ASG0002ujo,ASG0002gmz,ASG000rsqt,ASG000d45q,ASG000bd20,ASG000oigx,ASG00…
147	honeyBadger	ASG0002dip,ASG00038tl,ASG000397z,ASG000s8vx,ASG0011rxb,ASG000ackq,ASG000…
148	human	ASG000bkfb,ASG0011k06,ASG000aqd9,ASG0000ryh,ASG0000s87,ASG0008q3x,ASG00…
149	hyenaSpotted	ASG0000suv,ASG0006570,ASG000n4zw,ASG000sh6l,ASG000snet,ASG0006g8h,ASG00…
150	hyenaStriped	ASG00041tb,ASG00008ta,ASG000520y,ASG00070dv,ASG0003rd4,ASG000tqqi,ASG000…
151	impala	ASG0008l0r,ASG0011qw9,ASG00032i6,ASG000n244,ASG000rs4q,ASG000e8n2,ASG00…
152	jackal	ASG0000wun,ASG0003k6o,ASG0003uq0,ASG0000wur,ASG0001mby,ASG000y3sa,ASG…
153	koriBustard	ASG000c463,ASG0006i0x,ASG0003rb7,ASG0006if5,ASG0008oik,ASG0003k76,ASG000…
154	leopard	ASG000muxj,ASG0007qno,ASG00024zv,ASG0003ldz,ASG000ssu1,ASG000dcbb,ASG00…
155	lionFemale	ASG0003uuu,ASG000r7y5,ASG0001cqw,ASG00038hl,ASG00083jc,ASG000omwr,ASG00…
156	lionMale	ASG0005mgp,ASG0006aw0,ASG0004ygj,ASG0005mfa,ASG000qlj6,ASG000ttzh,ASG00…
157	mongoose	ASG0002hc5,ASG00003df,ASG000ai54,ASG0010pxf,ASG0010pxg,ASG000p9ic,ASG001…
158	ostrich	ASG0008o7y,ASG000myqb,ASG000s89g,ASG000s89h,ASG000t83h,ASG0008l2x,ASG00…

- For each user, we identified their two top species from TD-14, then picked 20 images at random (being careful to avoid duplicates) from the per-species sets shown above [“RECOMMEND SUBJECT SETS PER USER” in diagram above]. This combination of 40 recommended images constitutes the subject recommendations for that user [“SUBJECT RECOMMENDATIONS” in diagram above], which can then be used in a real world scenario such as TP-506-04 below.

RECOMMEND SUBJECT SETS PER USER - Pseudocode

```
for each user
  create a subject recommendation set
  pick the two species with highest score from TD-14
  for each favourite species
    pick 20 random subjects from the subject set for that species
    add these subjects to the recommendation set for that user
  next favourite species
next user
```

Testing approach

Testing again focussed on data quality - ensuring the subject recommendations contained the user’s preferred species. This was done as follows: We randomly selected 5 users and inspected their subject recommendations. We then looked at the user profile data (species preferences, TD-14) and inspected a random sampling of at least 20 subjects for each

user. We confirmed that the subjects' primary species were those species occurring in the user's two favourite species. This test was successful.

The KPIs planned (precision, recall, F1-measure) were not tested since we are no longer in a comparison to external known good data scenario.

The "changed behaviour" borderline case was tested in TP-506-03 below, see the next section.

TP-506-03 - Test that different species preferences result in the correct changes to subject recommendations

This test focussed on ensuring that changing user species preferences would result in a correctly updated set of subject recommendations.

The approach here was to create a modified version of the TD-14 user profiles (the modified version is referred to as TD-15). This was again done using a combination of MySQL queries and Python scripts.

For example, we would pick a user whose favourite species were zebra and giraffe, and switch them to lion and gazelle.

We then repeated the tests described for TP-506-02 above, but using TD-15 instead of TD-14, and inspected the recommended subjects to ensure the "modified" favourite species were present. This test was successful.

The KPIs planned (precision, recall, F1-measure) were not tested since we are no longer in a comparison to external known good data scenario.

TP-506-04 - Real-world tests using recommender results

The main purpose of building the subject recommendations was for use in this real world experiment, referred to as the "Happy User Experiment". This theorized that delivering users a subject set to classify that consisted more of "preferred" species than random species would result in greater engagement (defined in terms of session length and number of classifications per session).

The experiment consisted of splitting all visitors to Snapshot Serengeti into two groups - the control group (which continued to receive random subjects) and the "interesting" or experimental group which instead received a randomly-ordered subject set consisting of:

- 20 subjects recommended to match the user's top preferred species
- 20 subjects recommended to match the user's second preferred species
- 30 random subjects

So in essence, each user received 40 subjects chosen by the recommender system described above, and 30 random subjects. The subject set size of 70 subjects was chosen as it was sufficiently larger than the average session length of 23 subjects.

Further details on the experimental approach are outlined on the MICO blog here: http://www.mico-project.eu/snapshot-serengeti-season-8-ready-for-mico/

The experimental findings were published in detail on the MICO blog here:
http://www.mico-project.eu/snapshot-serengeti-an-unexpected-discovery/

We found that contrary to expectations, the average session length, and average classifications per session, were much lower for the experimental/"interesting" cohort. This showed us conclusively that giving users more of their preferred species does not have a positive impact on engagement; or at least, not with this subject set make-up.

This lead us to theorize that the reason for the lower engagement was that the "interesting" cohort users received fewer "blank" (no animals present) images, and that blank images play an important part in encouraging users to continue their classification efforts, probably much more than any effect of personalizing species to users. We went on to conduct further experiments into the impact of blank images; work-in-progress findings will be published at HCOMP 2015 in November, and are available here:

http://bit.ly/blanks-paper
http://bit.ly/blanks-poster

B1: Use Cases: First Prototype - Video News Showcase - Test Plan

Goals

We aim to compare each MICO TE prior to begin testing end-to-end the system. For each MICO TE included in these tests we're willing to asses:

1. **outputs accuracy** - how much each single response is accurate, detailed and meaningful in terms of precision/recall and eventually where MICO TE stand when compared to other similar technologies available in the market;
2. **technical performances** - how much time each single task requires and how scalable the solution is when we increase in volume the amount of contents being analysed;
3. **usability** evaluated both in terms of **integration** and **modularity** when we add these technologies to our existing workflows.

Technical performances will be measured in terms of:

1. **latency** - time required to perform a single task on a given dataset. Measures will be repeated 10 times;
2. **scalability** - it the given TE suitably efficient and practical when applied to large situations (e.g. a large input dataset and / or, a large number concurrent requests). External platform as LoadImpact **[REF-LI]** could be used.

Usability

The TE usability requires a qualitative evaluation which will consider:

- **integration** - how simple it is to integrate each single TE within pre-existent application workflows;
- **modularity** - how simple it is to configure each TE and/or a combination of multiple TEs in a chain from within pre-existent application workflows.

Test Implementation Plan

ID	Test	Description
TP-204-01	**Test in-front face detection on images**	● use dataset **TD-01** ● process **TD-01** with TE-204 ● calculate precision, recall and F1-measure on TE-204 outputs. ● process **TD-01** trough **BetaFaceApi** [REF-BS-01] ● calculate precision, recall and F1-measure on TE-204 outputs. ● compare **KPIs**
TP-204-02	**Test lateral face detection on images**	● use dataset **TD-02** ● process **TD-02** with TE-204 ● calculate precision, recall and F1-measure on TE-204 outputs. ● process **TD-02** trough **BetaFaceApi** [REF-BS-01] ● calculate precision, recall and F1-measure on TE-204 outputs.

		• compare **KPIs**
TE-214-01	**Test ASR on videos containing voiceover in english without noise and/or music**	• use dataset **TD-05** • process ASR on **TD-05** via TE-214 • calculate **Word Error Rate (WER)** on **Automatic Speech Recognition (ASR)** results transcriptions in D-05 as reference. • process ASR on **TD-05** via **Vocapia** [REF-BS-03] • calculate **WER** on ASR results transcriptions in D-05 as reference. • compare **KPIs**
TP-WP05-01	**Item similarity based use case test**	• use dataset **TD-03** • train WP5 on **TD-03** • query WP5 to generate recommendation for each item in D-03 • calculate precision, recall [REF-PR] and F1-measure [REF-F1] for each WP5 outputs.
TP-WP05-02	**User based use case test**	• use dataset **TD-04** • train WP5 on **TD-04** - use 70% as training set, 30% as test set • calculate precision, recall [REF-PR] and F1-measure [REF-F1].

B2: Use Cases: First Prototype - Video News Showcase - Validation Report

Overview of Test Results

ID	Test	Summary of Test Results

TP-204-01	**Test in-front face detection on images**	• We've seen **MICO outperforming BetaFaceAPI** on the precision (49% vs 43%) while having the same level of performance in terms of recall (50%)
		• While the dataset was small we've gained enough confidence that MICO (adequately trained) can compete with commercial 3rd party cloud services
		• F-1 sees MICO at 49% and BetaFaceAPI at 46%
		• Both algorithms struggled to differentiate the drawing of a face (from a t-shirt of one of the supporter) from real human faces
		• The infrastructure for integrating MICO with WordPress and HelixWare has been produced and contributed:
		  ○ https://github.com/insideout10/mico-gateway
		  ○ https://github.com/insideout10/helixware-mico-plugin
		these modules have been designed for TP-204-01 and TP-204-02 and can also be used in TP-214-01
		• The experiment has produced a new tool that can help gather ground data and execute this kind of tests:
		  ○ https://github.com/insideout10/facedetection

TP-204-02	**Test lateral face detection on images**	• In this case precision and recall gets lower for both as faces are harder to detect. MICO has showed precision at 13% and recall at 13%, BetaFaceAPI performed better with precision at 19% and recall at 20% • The model for face detection of MICO has been trained with frontal faces (hence this result was somehow expected)
TE-214-01	**Test ASR on videos containing voiceover in english without noise and/or music**	• According to the tests MICO has an average WER (Word Error Rate) of 0.925 while Vocapia (a commercial provider of speech to text cloud services) has 0.627 • The WER rate might not necessarily have a great impact on the Entity Detection and further tests shall be performed in the next software iteration • As with other extractors training data (which may be acquired with more contents and time), the WER value of MICO can substantially improve • Since MICO supports multiple extractors, it is able to automatically extract the audio track from the ingested video assets without requiring any preprocessing from the client side (which is required by Vocapia which only accepts audio tracks of specific codecs and formats) • As noted by Björklund, Cleophas and Karlsson the use of probabilistic lexicalized tree insertion grammars for automatic speech recognition, in addition to the transcription produced by the Kaldi extractor could produce a parse structure valuable for our use case. This work is described in a paper by Björklund, Cleophas and Karlsson, presently to be submitted for publication.
TP-WP05-01	**Item similarity based use case test**	• WP5 components do produce plausible user-customized recommendations • Proposed test metrics are not appropriate for recommendation use cases, user studies will be necessary that will be conducted for the final evaluation
TP-WP05-02	**User based use case test**	• WP5 components do produce plausible user-customized recommendations • Proposed test metrics are not appropriate for recommendation use cases, user studies will be necessary that will be conducted for the final evaluation

Details Test Reports

Due to time constraints, we could not complete our validation by re-using the integration components between our software tools (HelixWare, the Online Video Platform and WordLift the plugin for WordPress) and MICO as we had originally planned.

The first tests during evaluation phase infact revealed, that the MICO platform / extractors / tools and especially the rather complex pipeline (e.g. compared to the Zooniverse pipeline) were not mature enough to conducts such tests. While this was a drawback for the evaluation, it provided valuable input for platform (broker), extractor and development tools.

At the same time this forced us to keep the evaluation of each TE separated from the integration with our toolset, limited the engagement with our stakeholders (we had to work in our labs rather than having the end-users directly involved in the tests) and made us adopt a more classical evaluation approach. As time was limited we had to keep our test datasets smaller than planned.

Throughout the testing we had experience several issues that can be described as follows:

1. downtime and stability issues; platform not responding - hanging without providing any valuable information (in some cases we had to ask the team to restart the server while in others adding an automatic retry of the API calls was sufficient). As an example the command for retrieving the status of the analysis pipeline generated an exception and we had no means of understanding when the process was completed.
2. development delayed since the early versions had issues that needed to be fixed before our testing could actually being. The extracted metadata, when the analysis pipeline ran successfully, was there and, apart from the really early versions, also complete but tools used for retrieving the metadata were not all as mature as expected. For instance queries of annotations build with Anno4j did not provide any result or error information and eventually we decided to use queries in SPARQL.
3. the evaluation for functionalities like the face detection on videos posed the challenge of deciding at what level the extraction should work (i.e. *whole video*? *single shot*? or *key-frame*?). We planned to use the face detection to add the tag `people` to videos being ingested via HelixWare or Shoof and we had received from WP2 three options for running the face detection: video-keyframes, video-steps (one frame every 3 seconds) and images. While our contents was primarily videos in order to use quantifiable measures in the validation tests and reasonable effort for creating ground data we've opted for validated images instead of videos.

In other words we had to revise our testing strategy and adapt the testing to the available functionalities of the platform.

Background for TP-204-01 and TP-204-02: Face detection

We've began evaluating MICO in the context of media curation and filtering for two of our main use cases: the Greenpeace magazine and Shoof the micro-recording video app.

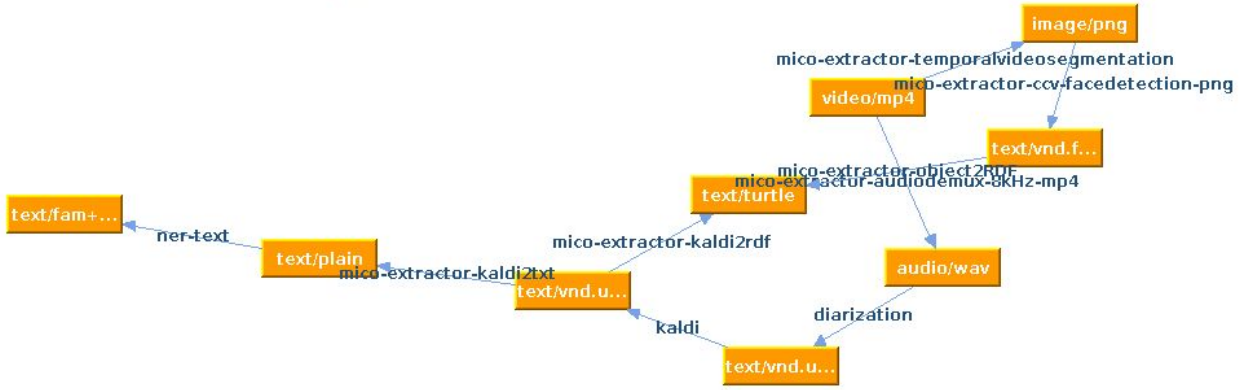
The basic idea behind this test is that for organisations being a non-governmental organization (NGO) like Greenpeace or a startups like Insideout Today (the company developing Shoof) a great effort is needed to curate and filter media assets.

Face detection is an important part of face recognition as the first step of automatic face recognition. Face detection allows us to classify content that contains human beings and also to

build interlinking between audiovisual and textual contents that share the same people (and possibly the same topic).

However, face detection is not straightforward because it has lots of variations of image appearance, such as pose variation (front, non-front), occlusion, image orientation, illuminating condition and facial expression. In this test we've been focusing our attention to front face detection.

While our goal is to detect faces in videos (and we have two pipelines in MICO supporting this requirement) the test is based on a small dataset of images derived from the Digital Asset Manager of Greenpeace.



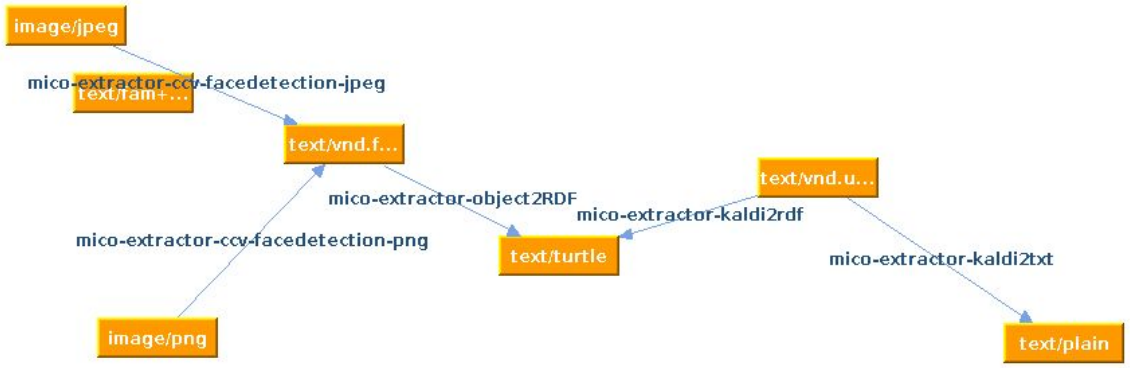
Pipeline combining temporal video segmentation, face detection and (ASR) automatic speech-recognition - takes in input a video

The analysis chain that combines face detection, temporal video segmentation with ASR works as follows:

1. audio-videos files are ingested (in our case from a WordPress front-end or via APIs)
2. the audio part is sent to Kaldi for the Automatic Speech Recognition
3. while the video part is sent to the temporal video segmentation
4. and the resulting images are processed by the face detection extractor

This pipeline is extremely complex, as explained above, we've decided instead to use images for the evaluation rather than videos. Using images helped us compare MICO with other systems and provided a quantifiable measurement for the testing.

Here follows a diagram representing the pipeline used for the testing (as seen from the MICO broker admin interface).



Pipeline providing face detection on images

The face detection extractor was deployed starting from June 2015 and had subsequent releases. The extractor, developed by the Fraunhofer team, is using an open source library (CCV - http://libccv.org) and has been trained for in-front faces so we expected better results on TP-204-01 rather than on TP-204-01 (that first test is for in-front faces and the second is for lateral faces).

Results Summary

In the tests the definitions used are:

- True positive: faces correctly identified (including any intersects)
- False negative: faces incorrectly identified as not present
- False positive: faces incorrectly identified (intersect = 0)
- Precision: the percentage of faces identified by the system that are indeed faces (intersect > 0%)
- Recall: the percentage of correctly identified faces among the total number of faces that are present in the dataset.

Here is a snapshot of the results of the test accuracy in terms of precision, recall and F-1 measure **combining in-front and side face detection**:

BetaFaceAPI

Precision	Recall	F-1
0.2903225806	0.3214285714	0.3050847458

MICO

Precision	Recall	F-1
0.2743362832	0.2767857143	0.2755555556

MICO for in-front face detection outperforms BetaFaceAPI and proves to be immediately usable in our showcase. The side detection of MICO is poorer than BetaFaceAPI (therefore the combined results are affected) - in both cases, when dealing with side faces, the complexity is much higher and the overall accuracy is low.

Evaluation Approach

In order to asses the quality of the analysis provided by MICO we need to know if and where each face is positioned within each image. Moreover, as a startup willing to bring these functionalities in our product line, we want to make sure the quality of the results is comparable to existing solutions available in the commercial world.

As we needed to manually annotate the dataset composed of 60 images (30 for in-front faces and 30 for later faces) and to confront the result of MICO with the results from a commercial provider we decided to develop a web tool for automating the task.

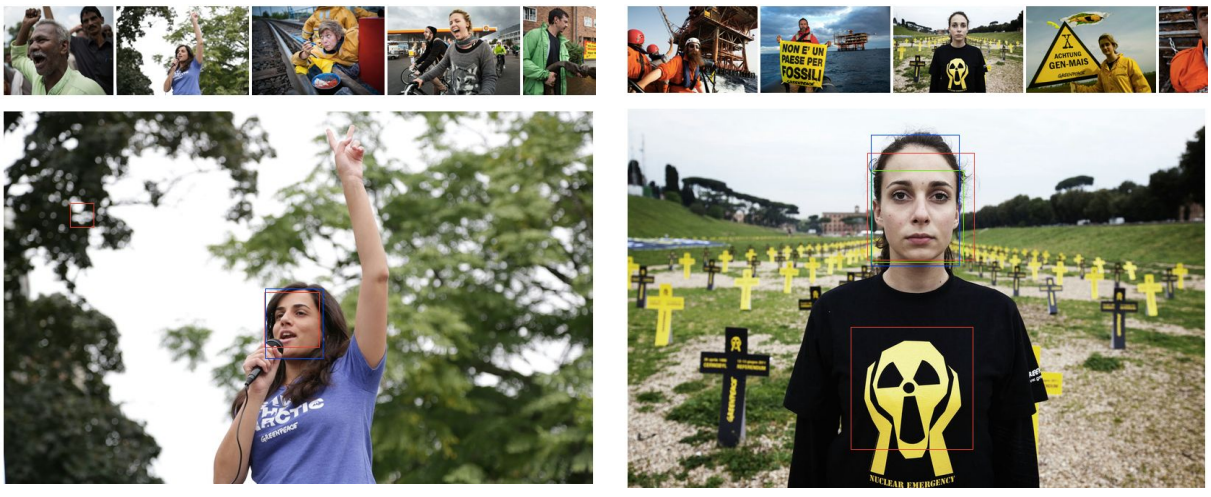
While for a statistical robust evaluation we would have needed a much larger dataset the changes in our evaluation strategy (from testing in an integrated / live scenario to a classical evaluation approach) had forced us to keep the number of items very low at this stage. Building a web tool, on the other end, was a good move as we can now scale up these datasets and continuing the evaluation work on the next platform iterations.

The tool has been contributed as open source and is available on GitHub:

- https://github.com/insideout10/facedetection

The third party service providers we've used for the benchmarking is BetaFaceApi (http://betafaceapi.com) a commercial SaaS offering face detection and face recognition in the cloud (their pricing starts at `0.035 EUR` per image).

Here are two screenshots of the tool we've created for the testing.



The tool has been designed with the purpose of executing the following tasks:

1. upload the dataset of images

2. manually annotate the images using a rectangular-shaped selector - the color of the manual annotation is blue
3. sending each image to BetaFaceAPI and to MICO
4. handle exceptions from MICO and retry sending the image after 3 seconds
5. receive the analysis results from BetaFaceAPI and add a red annotation on each image
6. receive the analysis results from MICO and add a green annotation on each image
7. store all corresponding media fragments as separate image files
8. store the coordinates of each annotation (manual, BetaFaceAPI and MICO)
9. calculate overlaps, KPI test results and export it to CSV

The tool uses:

- backbone.js for the manual annotations
- Apache Camel for handling the analysis over to BetaFaceAPI and MICO
- HATEOAS (Hypermedia as the Engine of Application State) to navigate the REST APIs

For further refining the results of this test we are also planning to update the tool for implementing a new existing definition of True Positive in order to have:

- intersection (region_annot, region_gt) / union (region_annot, region_gt) >= 0,5

The results of this evaluation are also accesible on: http://facedetection-mico.insideout.io.

Test Framework Used

We used the MICO Platform API that was setup and managed by the team at Salzburg Research. See http://mico-project.bitbucket.org/api/ or document D6.2.2 for further details of custom animal detection and text analysis endpoints.

Using this API, the IO10 team has worked in three directions:

1. implement MICO functionalities in our existing workflows for HelixWare and WordLift
    a. this has provided an in-depth understanding of the existing strength and limitations of the platform in terms of integration effort required by a third party willing to leverage on MICO existing functionalities
2. engaging with our existing clients to understand at best their requirements and how MICO can bring concrete advantage within their operations - Greenpeace Italy on one side and the Shoof team on the other
    a. on this front, the complexity of the analysis pipelines we use, the overall maturity of some of the querying tools and the overall instability of the system, as presented above, limited the degree of integration between MICO and our software modules
3. test and evaluate the accuracy of the extractors being used in our showcase accordingly to the test plan designed within WP7 and WP8

TP-204-01 - Test in-front face detection of images

For this test we wanted to asses the quality of the annotations provided by MICO for Face Detection against a dataset of images from the Greenpeace DAM containing in-front faces.

The annotations derived from MICO and BetaFaceAPI have been analyzed against manually annotated faces (with a margin of error +/- 0.01%).

Metrics for the in-front face detection set

For testing the correct detection of a face, we defined the metrics below:

- Relevance is defined as “There is a face”
- Intersection is defined as “The system annotation intersects with the manual annotation”
- This leads to the following definitions:
    - True positive: faces correctly identified (including any intersects)
    - False negative: faces incorrectly identified as not present
    - False positive: faces incorrectly identified (intersect = 0)
    - Precision: the percentage of faces identified by the system that are indeed faces (intersect > 0%)
    - Recall: the percentage of correctly identified faces among the total number of faces that are present in the dataset.
    - F1 score: overall measure of this test’s accuracy, combining precision and recall

- Results are available online in a Google Spreadsheet: https://goo.gl/LcALKQ
- A selection of faces detected by BetaFaceAPI is provided over here as an example: https://goo.gl/yxtKic

As we expected for in-front faces **MICO outperformed BetaFaceAPI and proved to be immediately useful in our showcase.**

Results from MICO

	Quantity	True Positive	False Positive	False Negative	Precision	Recall	F-1
Frontal	44	22	1	22	0.4888888889	0.5	0.4943820225

Results from BetaFaceAPI

	Quantity	True Positive	False Positive	False Negative	Precision	Recall	F-1
Frontal	44	22	7	22	0.431372549	0.5	0.4631578947

TP-204-02 - Test lateral face detection of images

For this test we wanted to asses the quality of the annotations provided by MICO for Face Detection against a dataset of images from the Greenpeace DAM containing side faces (usually much harder to detect than in-front faces).

As for the previous tests annotations derived from MICO and BetaFaceAPI have been analyzed against manually annotated lateral faces (with a margin of error +/- 0.01%).

Metrics for the side face detection set

For testing the same metric of TP-204-01 have been used.

- Results are available online in a Google Spreadsheet: https://goo.gl/LcALKQ

As the detection model behind MICO was not trained for side faces BetaFaceAPI outperforms MICO but; in both cases the accuracy (F-1) is quite low.

Results from MICO

	Quantity	True Positive	False Positive	False Negative	Precision	Recall	F-1
Side	68	9	0	59	0.1323529412	0.1323529412	0.1323529412

Results from BetaFaceAPI

	Quantity	True Positive	False Positive	False Negative	Precision	Recall	F-1
Side	68	14	5	54	0.1917808219	0.2058823529	0.1985815603

Background for TP-214-01: Automatic Speech Recognition

The main goal of TE-214 Automatic Speech Recognition (ASR) in our showcase is to be able to interlink audiovisual contents with text articles.

An editor using WordLift (a semantic editor for WordPress that is being used by Greenpeace for their online magazine website) has access to a large amount of video contents via the internal digital asset manager. The amount of time required to properly filter and select a video to enrich an article is though too high and in most cases incompatible with the tight publishing schedule of the organisation.

Also for the editorial team that will work behind Shoof (the micro video-recording application) filtering and moderating user-generated contents can be extremely costly and time consuming. The use of ASR in MICO for our showcase is therefore not intended to generate readable transcripts but to help editors working with Content Management System and Digital Asset Managers quickly scan, filter and interlink media files with other contents (primarily news).

Evaluation Approach

As for the face detection also for ASR it is important to us to ensure the quality of the results of MICO is somehow comparable to what we can achieve with commercial service providers offering this functionality in the cloud.

Following the expert advice of MICO transfer partner CodeMill AB for this test we've chosen to compare MICO analysis results with Vocapia (http://www.vocapia.com/) a provider of speech-to-text software services.

The testing has been done using an open source Java class that aligns two string sequences and calculates the word error rate (WER) - the metrics we've chosen for this test. The library is available on https://github.com/romanows/WordSequenceAligner.

Metrics for testing ASR

The tests used the Word error rate (WER), a common metric of the performance of a speech recognition or machine translation system. The general difficulty of measuring performance lies in the fact that the recognized word sequence can have a different length from the reference word sequence (supposedly the correct one).

The WER (as by definition of Wikipedia) is derived from the Levenshtein distance, working at the word level instead of the phoneme level. The WER is a valuable tool for comparing different systems (MICO and Vocapia in our case) as well as for evaluating potential improvements within TE-214 (the Kaldi extractor responsible for the automatic speech recognition in MICO).

TP-214-01 - Test ASR on videos containing voiceover in English without noise and/or music

Here follows the list of files in **TD-05**. We've chosen a selection of videos with subtitles in English stored in a separate .srt file. These videos have been taken from the Greenpeace

worldwide digital asset manager. While each video contains some voiceover in English it was hard to find videos completely without noise or music.
The size of the dataset is relatively small in this case as for TP-204-01 and TP-204-02.

Test results

It is worth mentioning that while in MICO the extractor is using a standard model for English the ASR provided by Vocapia had a specific settings for British English.

ID	A/V Filename	CC Filename	MICO WER	Vocapia WER
1	An_upload_from_Santa_himself_Christmas_2013_might_be_cancelled	An_upload_from_Santa_himself_Christmas_2013_might_be_cancelled_audio.ref	1.7361112	1.0833334
2	BREAKING_Shells_Arctic_oil_rig_in_sight	BREAKING_Shells_Arctic_oil_rig_in_sight_audio.ref	0.6785714	0.4945055
3	EXPOSED_Santander_loaned_millions_to_the_company_that_did_this	EXPOSED_Santander_loaned_millions_to_the_company_that_did_this_audio.ref	0.810219	0.5985401
4	Fukushima_Four_Years_On	Fukushima_Four_Years_On_audio.ref	0.8531856	0.66759
5	Ice_Ride_the_global_bike_ride_to_defend_the_Arctic_Are_you_in	Ice_Ride_the_global_bike_ride_to_defend_the_Arctic_Are_you_in_audio.ref	0.9219858	0.6312057
6	Living_For_A_Cause_1_Kumi_Naidoo	Living_For_A_Cause_1_Kumi_Naidoo_audio.ref	0.8073879	0.66490763
7	Stephen_Tindale_Former_Greenpeace_UK_Executive_Director_Nuclear4Climate	Stephen_Tindale_Former_Greenpeace_UK_Executive_Director_Nuclear4Climate_audio.ref	0.8577778	0.5688889
8	Thank_you_from_Greenpeace_volunteers_on_Shells_rig	Thank_you_from_Greenpeace_volunteers_on_Shells_rig_audio.ref	0.88142294	0.66007906
9	The_Rainbow_Warrior_comes_to_London	The_Rainbow_Warrior_comes_to_London_audio.ref	0.90618765	0.7205589
10	The_Root_of_the_Matter_FSC_Greenpeace_and_Intact_Forest_landscapes	The_Root_of_the_Matter_FSC_Greenpeace_and_Intact_Forest_landscapes_audio.ref	0.79647434	0.6383547
		Average	0.924932363	0.672796389

The speech-to-text analysis results are available here:

- https://goo.gl/ywCypa

Latency

In our environment videos are sent to HelixWare (the online video platform) and from there to MICO for content analysis. As different analysis pipelines can be chained one to the other (hence increasing the amount of time required for analysing an asset) we've implemented a job queue via AMPQ. This way HelixWare calls MICO with batch processes that run independently and asynchronously.

Whenever an asset is received, or by user request, HelixWare starts a job configured to run a specific task and the task might be simple or complex (e.g. a Speech-To-Text task or a sequence detection task).

The job tracks the status, whether the activity has started, is progressing, is completed and results have been received; it also deals with multiple nodes, which one is going to handle the job, whether distributed communication is involved.

The task represents the actual data protocol which is required in order to provide something to process and what kind of response is expected (e.g. for a speech-to-text task, a response is expected that contains the transcribed text along with markers about the timecodes to sync the text with the video and eventually who's speaking).

Due to the blocking problem related to the missing of status information from MICO (no means of understanding when an analysis complets) we were not able to asses - during our evaluation tests - latency measured as the time interval occurring between the submission of the image and the reception of the analysis results.

Throughput

We've seen MICO coping with multiple parallel submissions, which means that in practice we could send up to 3 videos in a row without crashing the system. From the architecture point of view the MICO broker seems capable of scaling. As of today testing the throughput doesn't really makes sense due to the existing stability issues.

Stability

During the testing for this evaluation, MICO was constantly crashing and out of service. This meant that we struggled to get the results for this report even with small datasets like the ones we've used here (60 images and 10 videos). This is a critical aspect that needs to be addressed before we would be able to concretely use the platform in our showcase.

Modularity

The main issue here is related to the fact that we can use right now in MICO only one active extraction pipeline at the time. Either we decide to detect faces or we extract information using

ASR. While the new version of the broker shall overcome this limitation we've managed with the support from Fraunhofer to configure a complex pipeline combining temporal video-segmentation, face detection and ASR. This *all-in-one* approach clearly increases latency and aggressively decreases the platform stability (hence it cannot be used yet in production environments).

Integration

We decided to evaluate the integration of MICO in our existing toolset and we've been documenting the code required for interfacing MICO in terms of:

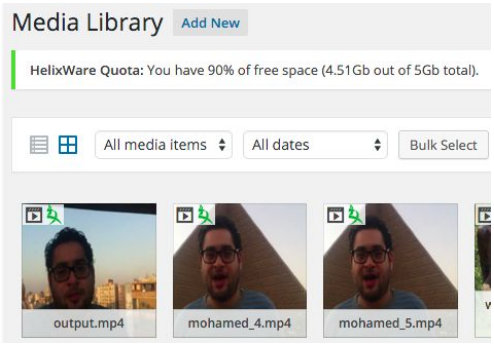
- Publish content items to MICO
- Start processing the content item
- Get an initial status report on the processing state
- Extract an initial set of metadata to be integrated within the application

This steps are fully documented here:

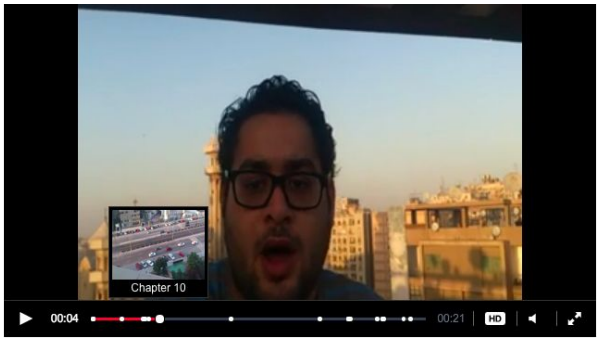
- https://goo.gl/UmjecN

As our original plan was to evaluate MICO in the real-world showcases we've built the following modules to integrate MICO with HelixWare and WordPress. The following contributions are open source:

- **MICO-Gateway** (https://github.com/insideout10/mico-gateway): based on the steps described above and for the purpose of interfacing MICO with HelixWare we've developed this component that can be used for helping others integrating with MICO in Java.
- **HelixWare MICO extension for WordPress** (https://github.com/insideout10/helixware-mico-plugin): this plugin extends the existing integration of HelixWare with WordPress to bring the result of the analysis privided by MICO to the CMS editor. The plugin is designed for the Greenpeace magazine use case and might also use for Shoof.



1. Media assets created with Shoof appear in the standard WordPress Media Library and from there are sent to HelixWare for encoding and to MICO for analysis.



2. The player embedded in the webpage using a WordPress shortcode displays the video including the chapters resulting from MICO TE-206 (temporal video segmentation).

Usefulness

We expect to leverage on the the results on MICO to extend the functionalities of our online services and software. We strongly believe RTD effort like MICO shall bring concrete advantages to startups like ours and to the developer community at large.

We will therefore continue to do our best to make this happen. As of today we've seen some concrete values in the provided extractors - the distance between MICO and commercially available services is not extreme - and, at least in our opinion, can be further reduced within year 3 of the project.

The overall platform and the testing we've done so far represent an overall positive outcome for MICO.

TP-WP05-01 and -02 - Item and User based use cast tests

Part of the test plan was to assess the performance of Work Package 5 on the Greenpeace magazine showcase. TP-WP05-01 covers recommendation on the basis of item similarity, i.e., content based recommendation, TP-WP05-02 covers recommendation based on user behaviour data, i.e., recommendation based on collaborative filtering.
Due to delays in WP5, only the collaborative filtering part was tested, while the testing of a combined recommendation using content analysis and collaborative filtering will be tested in the final use case validation. While the platform is capable of producing NER results from Video input – as required by this test plan – the required preprocessing to make it usable as recommendation source was not done.

However, the User Stories the test plan derives from can be covered by collaborative filtering only: Recommendation for registered users (mapping user-ids to item-ids) and recommendation for unregistered users (mapping item-ids to item-ids). The user based recommendation is used as a base function, the item based recommendation is interpreted as the succession of searching a user that has positive interest in the current item, and recommend items based on his profile.

The current system takes a list of google analytics data like TD04 and returns a ranked list of items as a recommendation, using prediction.io behind the scenes.
TD04 contains of 1926 Data point of the form (Date, UserType, PagePath, PageViews) with 699 different user ids. TD03 consisted of annotated data of some Greenpeace articles that have not been used to the reasons stated above.

The test plan provides for a measurement of precision and recall (and F-measure as a combination of both) on a split test data set. Those are well established tools in the machine learning society for that purpose. However, recommendation problems have a slight different nature than classification problems, which makes it hard to apply those metrics. Both precision and recall are very hard to determine. The process of recommendation is to find *something* that is *interesting* to the subject. This may change over time, even during the time the user is reading an article. As measuring the recall requires to know the amount of items that were interesting, but have not been recommended is even for small item sets a challenging task.

Similar arguments are valid for the evaluation of the Precision of a recommender. Usually, the recommendation logic is re-used for validation, the recommendation system clusters item using a certain set of rules. At validation stage, it is tested that those rules still apply. Due to the subjectivity of the recommendations, those rules will never be 100% correct. In other words: it is very hard to evaluate recommendation systems, as it is not possible to get reliable ground truth data for it. Even assuming there is such data, the popular scheme of k-folds validation is problematic, as the input data consist of time series data with data points that are highly dependent. Splitting a set might cover the semantic relationships that provide a good validation. Prediction.io integrates an evaluation framework that allows to evaulate using the “machine learning approach”. While it is easy to get numbers out of it, it does not provide a meaningful recommendation.

Still, the evaluation of the recommender system is possible, but not using the proposed 70%-30% cross validation, but by measuring the recommender quality indirectly using user studies as discussed in section *8.2.3 Online Evaluation* of the *Recommender Systems Handbook* by Ricci et.al.
When the Mico recommendation engine is deployed to the Greenpeace Magazine website, it is possible to measure the click rates on the provided recommendation. Using A/B testing, it will be possible to measure, how end user acceptance, i.e., recommendation quality, differs using different settings of the recommendation engine. Additionally, the recommender performance can be compared to the “random recommender”. Whether criteria like “Freshness” of the articles have an influence can be tested as well.
Additionally, asking a closed user group the recommendation will help to further fine tune the recommendation. We propose to conduct this research for the final use case validation, as it was not possible to conduct those measurements now.
Even if the test methodology is right, the evaluation results still might be ambiguous: The scope of articles inside the Greenpeace Magazine is very narrow. It is unlikely that there will be “wrong” recommendations at all, except for cases that might be ruled out programmatically (presenting articles, the user already read, presenting technically faulty items).