Predicting Visible Terms from Image Captions using Concreteness and Distributional Semantics

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Abstract: Image captions in scientific papers usually are complementary to the images. Consequently, the captions contain many terms that do not refer to concepts visible in the image. We conjecture that it is possible to distinguish between these two types of terms in an image caption by analysing the text only. To examine this, we evaluated different features. The dataset we used to compute tf.idf values, word embeddings and concreteness values contains over 700 000 scientific papers with over 4,6 million images. The evaluation was done with a manually annotated subset of 329 images. Additionally, we trained a support vector machine to predict whether a term is a likely visible or not. We show that concreteness of terms is a very important feature to identify terms in captions and context that refer to concepts visible in images.

1 INTRODUCTION

In the NOA prject, we collected over 4.6 million images from scientific open access publications. The nature of this image collection is completely different from classical image collections, as a large proportion of the images are close ups, X-Rays and CRT-scans, etc. Thus image recognition is not a solution to annotate these images and make them available for retrieval. Instead we select words from the image captions and from sentences referring to the image. We need to include sentences mentioning the image since in many publications the captions are extremely short and do not contain any terms referring to visible concepts. Annotation of the images with good keywords is in turn important to organise the images and to enable efficient search.

Image-caption pairs in scientific publications differ in two ways from image-caption pairs in most datasets. In the first place the nature of the images is different from the kind of images in most image analysis datasets (see e.g. Figure 1). In the second place, in most datasets we have captions that describe the image. In terms of Unsworth's taxonomy (Unsworth, 2007), the image and the caption are concurrent. For most image-caption pairs extracted from scientific publications the image and the caption are (at least partially) complementary and usually the text extends the image. E.g. in Figure 2 we see that the caption gives a lot of additional information that is not present in the image.

In a text that is complementary to the corresponding image we will find terms that refer to concepts visible in the image and terms that do not refer to depicted concepts but deal with the additional, complementary information. In the rest of the paper we will call the former ones **visible terms**.

We believe that the text in a complementary image-text pair gives some clear cues, what words are visible terms and which are not. Besides typical patterns to refer to concepts in the image, we expect to see word concreteness (Paivio et al., 1968) as a key feature to identifying these words. Thus, our main hypothesis is, that for image-caption pairs in which text and image are complementary, concepts in the text represented by words with high concreteness values are likely to appear in the image as well.

To verify this hypothesis, we used our corpus of over 710 000 scientific papers to train word embeddings and generate values for concreteness and idf. These where then tested on a manually annotated collection of 239 images trying to predict, what terms from the caption and from the surrounding text describe objects visible on the image. We do not analyse the image in any way, but just want to understand the text and get cues to find out which terms describe the image and which terms give additional information. It turns out that concreteness of a term is an important

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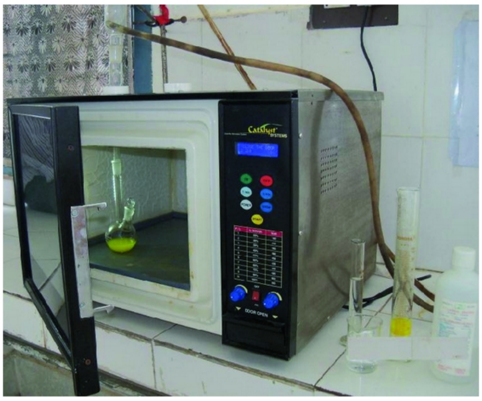
Image

Caption
Photographs displaying microwave irradiated synthesis of titled compounds.
Terms
photograph, **microwave**, derivative, reaction time, result, water, heat, substance, wall, solvent, energy, molecule, **mixture**, rise, temperature, thermal conductivity, superheating, rotation, radiation, research, biginelli reaction, thiourea, attempt, powers, final product, targets, chloroform, ethyl acetate, factor, ranges, spectrum, absorption band, region, stretching, vibration, proton, signal

Figure 1: Image and caption from *Sahoo, Biswa Mohan et al. "Ecofriendly and Facile One-Pot Multicomponent Synthesis of Thiopyrimidines under Microwave Irradiation", Journal of Nanoparticles (doi:10.1155/2013/780786)*. With terms extracted from caption and sentences referring to the image. The bold terms were identified by the annotators as terms representing concepts visible in the image.

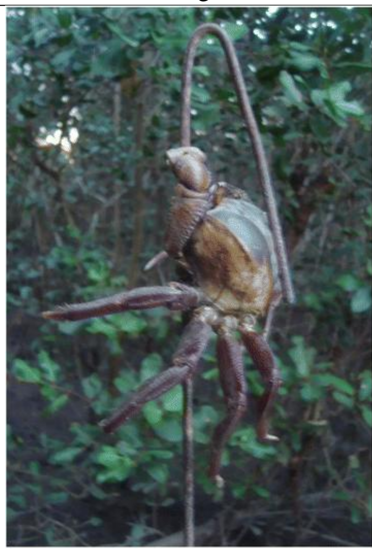
Image

Caption
Fig. 2 Metal pole (hook) used to pull the crab out by the catchers in Mucuri-Bahia State
Terms
figs, **metal**, poles, **hook**, **crab**, catcher, length, burrow, productivity

Figure 2: Image and caption from *Firmo, Angélica M.S. et al. "Habits and customs of crab catchers in southern Bahia, Brazil", Journal of Ethnobiology and Ethnomedicine (doi:10.1186/s13002-017-0174-7)*. With terms extracted from caption and sentences referring to the image. The bold terms were identified by the annotators as terms representing concepts visible in the image.

predictor for a term to appear in the image. Moreover, we see that inverse document frequency is not a good predictor.

After discussing the related work in section 2 we present our dataset in section 3. In section 4 we describe our approach how to select visual concepts followed by a description of our results and finish in section 6 with our conclusion and future work.

2 RELATED WORK

Unsworth (2007) studies the relations that can exists between text and images and defines a classification of image-text relations. These classes are investigated in detail in (Martinec and Salway, 2005) and (Otto et al., 2019).

Concept detection in images and automatic caption generation is a very popular field of research. A widely used dataset with image-caption pairs is Microsoft COCO (Lin et al., 2014). In this dataset all captions were written as descriptions of the image. Thus, these captions are not comparable to captions in scientific papers. In fact, for COCO we can assume, that each term mentioned in the caption refers to a concept visible in the image: the relation between image and text in COCO and similar datasets is a very specific one, not suited to verify our hypothesis.

A huge amount of research was done on image analysis and object and keyword detection using image data. This is not the topic of the present paper. For an overview of work in this area we refer to (Zhao et al., 2019), who provides an overview of state of the art methods of object detection with a focus on deep learning.

Our goal to identify words referring to depicted terms is most similar to keyword extraction. Algorithms for keyword extractions are well researched. Turney (2000) and Frank et al. (1999) used a decision tree to extract keyphrases based on various features indicating the importance of a term. Besides the classic features for salience and importance, inverted document and term frequency Salton et al. (1975), they also introduce new features like the position of a word in the text and features indicating the ’keywordness’, the suitability of a word as keyword.

Srihari et al. (2000) developed a multimedia information retrieval system, using various textual and visual features from the images as well as from their caption and context. For the image they used face detection, colour histogram matching and background similarity. From the text they extract named entities and picture attributes using Wordnet and tf.idf weighting. Gong et al. (2006) collected 12,000 web pages with images which were annotated by 5 experts for their topic. They select keywords for images by combining the importance of a word in a text block and the distance between the text block and the image. Gong and Liu (2009) extend this idea and add features from the images, especially textures generated by a Daubechies wavelet transformation and a HSL color histogram. These were then used to get positive and negatives sets of images for words using a Gaussian Mixture Model.

Leong and Mihalcea (2009) and Leong et al. (2010) explore the possibility of automatic image annotation using only textual features. They use features from the text, like frequency (tf.idf) and the part of the text in which the term occurs, as well as features of terms computed on other datasets, like Flickr and Wikipedia. These features should help to determine what words are suited to describe images. Leong and Mihalcea (2009) coin the likelihood of a term to be used as an image tag on Flickr the *Flickr picturability*. Flickr picturability seems to be very similar to concreteness and visualness, two well studied properties of words that are discussed below and that we will use to extract terms from captions. The main difference to our work is the different nature of web images and images from scientific papers. Flickr picturability does not fit to our data, while concreteness is a more general, domain independent concept and also not dependent on a commercial black box API.

An important indicator for the likelihood of a concept to appear in an image is the visualness of a concept as pointed out by Jeong et al. (2012). Visualness, often also called *imageability* or *imagery*, has been studied extensively for decades in the psycholinguistic community. Friendly et al. (1982) define visualness as the ease to which a word arouses a mental image when perceived. Visualness is one of the so called affective norms that were determined experimentally for many words. Many studies have shown a very high correlation between visualness and concreteness (Paivio et al., 1968; Algarabel et al., 1988; Clark and Paivio, 2004; Charbonnier and Wartena, 2019). Since much more data are available for concreteness, we will use concreteness rather than visualness below. Brysbaert et al. (2014) describe concreteness as the degree to which a concept denoted by a word refers to a perceptible entity; Similarly, Friendly et al. (1982) define concrete words as words that "refer to tangible objects, materials or persons which can be easily perceived with senses". With the help of distributional similarity between words or word embeddings as features for words, it is possible to predict the concreteness of words using supervised learning algorithms with a very high accuracy (Turney, 2000; Charbonnier and Wartena, 2019).

Concreteness has been used before in multimodal datasets. Kehat and Pustejovsky (2017) use the occurrence of words in such a dataset to predict the concreteness of words. Similarly, Hessel et al. (2018) determine a dataset specific concreteness for words using image-text relations and show that retrieval performance is higher for more concrete concepts.

3 DATASET

The dataset that we use for training contains full texts from over 710k scientific papers and over 4.6 million images and their captions from these papers. For evaluation 329 images from this collection were manually annotated with concepts that are visible on the image (visual terms) and general keywords that describe the image but that are not necessarily depicted directly.

3.1 Source and Selection

In the NOA project 4.608 million images from 710 000 scientific publications were collected Most images are charts, graphs, CT-scans, microscopy images etc. About 10% of the collected images are photographs (Sohmen et al., 2018). For each image we took the image caption and all sentences with a reference to that image. It was necessary to extend the captions with referring sentences for two reasons. In the first place in many publications the captions are too short, consisting just of two or three words. In the second place, even if the caption is meaningful, the context might give additional synonyms and related terms that can be helpful for further processing. From these extended captions we selected all terms that are used as a title of an article in the English Wikipedia. Thus, terms can be a single word or consist of multiple words. The average number of terms extracted for the images in the annotated data set is 25.22. The number of terms per image ranges from 2 to 226. Table 1 gives the numbers of terms extracted from the original captions and from the context.

From the extracted terms the annotators selected visible terms and keywords. In most cases the overlap between keywords and visible terms is very low: the average Jaccard coefficient between keywords and visible terms is 0.029.

3.2 Annotation

The images were annotated by two student assistants. Only images that were classified as photographs were presented to the annotators. The annotators were asked to select visible terms from a list of candidate terms and keywords, that do not necessarily denote depicted concept, but are suited to characterise the image as a whole.

The main guideline for selecting visible terms was to select any term denoting a concept or thing that is easily and clearly locatable on the image. I.e. there should be a clear region on the image depicting the term. E.g. if we have a picture of a bride and a groom in a church, we can identify a bride, a priest, etc., but not a wedding. However, wedding would be a good keyword. Usually objects, people, animals etc. or parts of those turn out to be good candidates for visible terms. On the other hand adjectives usually are not suited as visible terms. Also general terms like *object*, *structure*, *sphere*, *surface*, *coloured* are usually not suited.

The second instruction was, that interpretation and use of the common knowledge is allowed. If there is e.g. a human with a shepherd's crook, in front of sheep, the term *shepherd* is justifiable.

For keywords the annotators were asked to select terms that describe the image. Thus a term that is visible, but is not the main topic of the image should not be selected. Here more general and abstract concepts often fit very well.

The annotators were free to skip any image, but each annotator was obliged to annotate all images selected by the other annotator. We explicitly asked the annotators to skip images consisting of several sub-images and images containing text. Most other skipped images were not annotated because the annotators could not identify anything, either because of bad image quality or because they were not familiar with the technical objects on the picture. In total the annotators selected descriptive terms for 329 images. An example of an easy to annotate image with a small number of terms is given in Figure 2.

The complete dataset of annotated images can be downloaded from http://textmining.wp.hs-hannover.de/datasets. Table 2 gives an overview of the main characteristics of the data set.

The annotation process was perceived as extremely difficult and time consuming by the annotators, as they were unfamiliar with many specific scientific terms.

Initially, both annotators selected visible terms and keywords for each image. After this first annotation phase the inter-annotator agreement measured by Krippendorf's α (Krippendorff, 1970) was 0.57 for keywords and 0.58 for visual terms. Since the annotators felt uncertain about their annotations for the visual terms and were sure to have made many mistakes in the first annotations, we have shown them all images a second time. In this second phase they worked together, could discuss the annotations and remove incorrectly selected terms but not add new terms to their selection. The inter-annotator agreement for the visual terms after this correction phase is 0.78. In the following we will always use the union of the selected terms from both annotators, i.e. we consider a term as a good visual term (respectively keyword) if it was selected by one of the annotators.

4 SELECTING VISIBLE CONCEPTS

One of the most common methods to select characteristic terms from a text is to use the inverse document frequency (idf). This is in fact a kind of unsupervised learning, since the idf values of each term have to be computed on a collection of training data, but without any supervision. Other features can be computed in a similar way. In the classical supervised keyword extraction approach, discussed above, a supervised method is used to combine these features in an optimal way. This is of course only possible if enough training data are available. In order to investigate the potentials and usefulness of each feature, however, no training data are required and a smaller set of test data suffices. For keyword extraction from news texts or abstracts of scientific papers idf is known to be always one of the best features. In the following we will investigate whether this holds for image captions as well, or whether other features give better results.

In order to evaluate features, we rank the terms according to each feature and evaluate these rankings. For some features we have many terms that get a default value for that feature. In these cases we cannot sort the terms when we use only that feature. To solve this problem, we always randomly shuffle all terms with the same value.

Table 1: Average number of terms from caption and context per image.

	all data	annotated data		
	terms	terms	vis. term	keywords
caption only	6.15	3.31	0.29	0.45
context only	19.77	21.26	1.21	0.50
capt. + cont.	4.20	2.49	0.71	1.14
total	21.49	25.22	2.22	2.10

Table 2: Main characteristics of the data set of scientific images, captions, extracted and selected terms.

Number of images	329
Number of extracted terms	8296
Number of selected visual terms	729
Number of selected keywords	691
Number of annotators	2
Inter-annotator agreement (vis. terms)	0.78
Inter-annotator agreement (keywords)	0.57

IDF. We compute the inverse document frequency on the whole collection of 4.6 Million image terms, where the set of image terms for each image consists of all Wikipedia terms extracted from caption and referring text as described above. We compute the idf value for a term t as $\mathrm{idf}(t) = \log \frac{N-df(t)}{df(t)}$ where $df(t)$ is the number of documents containing t and N the total number of documents. As a feature we finally use the normalized idf-value, that is computed as $\mathrm{idf}_n(t) = \frac{\mathrm{idf}(t)}{\log N}$.

Caption Similarity. In the sentences referring to the image, but also in the caption, we might find words that are not representative for the caption. We measure the degree of representativity of a term t by computing the cosine of the word embedding of t and the averaged embedding of all words in the caption. For this purpose we computed word embeddings using word2vec (Mikolov et al., 2013) on the full text of over 2 million papers in our collection.

Concreteness. We assume that concrete words in the caption are more likely to refer to concepts depicted in the image than abstract words (see also section 2). We compute the concreteness of each term using a model trained on the concreteness values for 37,058 words from (Brysbaert et al., 2014) as described by Charbonnier and Wartena (2019). If, for some reason, we have no word embeddings for a term, we cannot compute the concreteness and use the average concreteness over all words. For terms consisting of several words we use the maximum of all concreteness values of the individual words, assuming that a phrase becomes usually more concrete when we add additional information.

Pattern. Many captions explicitly mention what is depicted by using phrases like *Picture of an X*. In order to exploit this information we search for the regular expression:

```
(photograph(ie|y)?|ct|CT|view|scan|
picture|image)s? of (the|a|an)?
```

If both the pattern and a term t are found in the caption, we determine the position of the pattern, $\mathrm{pos_{pat}}$, and $\mathrm{pos}(t)$ the position of t in the caption. We use $\frac{1}{\mathrm{pos}(t)-\mathrm{pos_{pat}}}$ as the value for this feature. If either the term or the pattern is not found the value is 0. For most captions we do not find such a pattern and if the pattern is found, most words usually come from referring sentences and are not found in the caption. Thus this feature usually is 0. The pattern was found only in 18 of 329 captions and thus only can have a small impact on the overall result.

Position. We assume that image captions follow a structure where the beginning of the caption describes the visible content of the image and the end gives more explanation and back-ground information. Therefor we expect to find the best visual terms/keywords in the beginning of the caption and weight the terms relative to their position using $1 - \frac{\mathrm{pos(t)}+1}{\mathrm{len(caption)}}$. If the word is not found in the caption the value is set to -1, which is the case for a large fraction of all terms. The position of a word in a text is also a common feature for keyword extraction.

Source. As we can see in Table 1, terms that are found as well in the caption as in the context are extremely likely to be a keyword or a visible term. Thus we introduce a binary feature telling whether the term was found in one (caption or context) or in two sources (caption and context). Whether a term is found in the caption or not is already coded indirectly in the features *Position* and partially in *Caption Similarity*.

5 RESULTS AND DISCUSSION

5.1 Results

The effectiveness of each feature for extracting visible terms and key terms in the test set is given in Table 3 and 4, respectively. Here we report the Area under the ROC Curve (AUC) and precision and recall for the top 3 results. Furthermore, we also calculated Spearman's ρ rank correlation between the results given by each feature. These results are given in Table 5.

Table 3: Results for the prediction of visible terms. All values are averages with their standard deviations from the extraction for 329 captions.

Method	AUC	Prec@3	Rec@3
IDF	0.57 ± 0.23	0.16 ± 0.21	0.26 ± 0.38
similarity	0.67 ± 0.27	$\mathbf{0.26} \pm 0.26$	0.39 ± 0.49
concr.	$\mathbf{0.80} \pm 0.19$	$\mathbf{0.25} \pm 0.25$	$\mathbf{0.52} \pm 0.38$
pattern	0.52 ± 0.24	0.16 ± 0.21	0.25 ± 0.36
position	0.58 ± 0.25	0.22 ± 0.22	0.35 ± 0.38
source	0.64 ± 0.26	0.22 ± 0.22	0.37 ± 0.39

Table 4: Results for the prediction of keywords. All values are averages with their standard deviations from the extraction for 317 captions.

Method	AUC	Prec@3	Rec@3
IDF	0.64 ± 0.23	0.22 ± 0.24	0.34 ± 0.37
similarity	$\mathbf{0.74} \pm 0.24$	$\mathbf{0.35} \pm 0.27$	$\mathbf{0.49} \pm 0.37$
concr.	0.59 ± 0.25	0.20 ± 0.24	0.29 ± 0.35
pattern	0.54 ± 0.24	0.17 ± 0.23	0.26 ± 0.35
position	0.63 ± 0.26	0.29 ± 0.25	0.42 ± 0.36
source	$\mathbf{0.72} \pm 0.25$	$\mathbf{0.36} \pm 0.89$	$\mathbf{0.51} \pm 0.39$

5.2 Discussion

For the kind of image-text pairs that we consider, we find terms in the text (caption and sentences with an explicit reference to the image) referring to concepts visible in the image as well as to concepts not present in the image. Our hypothesis was, that we can distinguish these terms by analysing only the text. We did not find a single feature that perfectly separates the terms, but concreteness turns out to be a good predictor for the appearance in the image: In Table 4 we see that the ranking of terms only according to concreteness already gives an AUC of 0.80. For selecting good keywords concreteness is on contrary almost useless. If a term is mentioned both in the caption and in referring sentences, it seems indeed to be an important term for the image and is highly likely to be either a key term or a visible term. This feature is somewhat specific for images in scientific papers, where we always have a caption and explicit references to a figure. A further good and more general feature for both extraction tasks is the similarity of a word with the averaged word vector of the terms in the caption.

Table 5: Spearman correlation between results of each feature. For the binary features (pattern and source) results with the same value are ordered randomly.

	IDF	sim.	concr.	pattern	position
IDF	-				
sim.	0.328	-			
concr.	0.194	0.142	-		
pattern	0.017	0.010	0.004	-	
position	0.021	0.067	0.065	0.029	-
source	0.057	0.184	0.058	0.057	0.174

The regular expression described in section 4 is of course a strong indication if the pattern is present, unfortunately in most captions no matching pattern is found at all and thus this feature does not contribute a lot to the result. Nevertheless, in an application it is important to use this feature, as no user will understand that a term X is not present as descriptive term while the captions explicitly says that it is "a picture of X". The position of the word in the caption also seems to be informative, as was noticed in various studies on keyword extraction.

Interestingly, we see that inverse document frequency is not a useful feature for the extraction of visible terms. This contrasts almost all other applications of keyword extraction. The reason is clear, when we look at the images and captions in more detail: something quite general can be seen on the image, e.g., an oak forest, but the caption uses a lot of specific terms about experiments or observations not visible on the picture. In a concrete example of such an image (Figure 4 of https://www.hindawi.com/journals/isrn/2011/787181/) the caption contains the following phrase *... sites selected for sampling in the wildlife bovine TB transmission areas: (a) an oak forest where deer fecal pellets were collected; ....*

Finally, we see that almost all features are completely unrelated. For the binary features this is not surprising since all results with the same feature value were ordered randomly. Remarkable is the weak correlation between the binary source feature and the similarity of word embeddings from the keyword and the caption: both methods favor frequent words and words appearing in the caption over words only appearing in the context. The highest correlation is found between idf and the similarity feature. This suggests that the influence of salient words on the average word embedding of the caption is larger than that of common words.

5.3 Supervised Classification

Finally, we want to know how good a supervised classifier would perform combining all features. The amount of training data seems to be quite small. However, the number of features is small as well and as we consider the problem of selecting visible terms (and keywords) as a binary classification problem (each term has to be classified as being a visible term (or keyword) or not), we have enough instances to train and evaluate a classifier. As we have selected 8,296 candidate terms for all images (see Table 2, we have in principle 8,296 cases to train and evaluate the classifier on. Additionally, the features for idf, word embeddings and concreteness contain information from much larger datasets. We evaluate the classifiers per image-caption pair and compute typical measures like precision and recall per image, since the overall accuracy of course is very high due to the fact that almost every term is not a visible term (or keyword).

As a simple, but robust and usually good classifier we used logistic regression. We also trained Support Vector Machines (SVM). We used a rbf kernel with the following hyper parameters[1], both for classification of visual terms and key terms: $\gamma = 1 \cdot 10^{-2}$, $C = 10$. In order to rank the the binary classification results, we sort the terms according to the confidence scores given by the classifier.

The results for classification are given in Table 6.

If we compare these results to those in Table 3 and 4 we see that the combination of he features indeed gives better results. For the visible terms there is only a moderate improvement of the AUC over the result from concreteness only, emphasising again the strength of this feature.

If we take a closer look at the results, in many cases we find that the classifier selects a lot of terms that are too general. E.g. we have an image of a milling cutter and a setup for automatic visual analysis of a surface (https://www.hindawi.com/journals/JOPTI/2015/192030.fig.001b.jpg). Here only the term *machine* was selected manually. While machine is already very general, the classifier selects even more general terms: 'machine', 'wear', 'system', 'tool'.

Another frequent type of error is, that the classifier predict too many terms, as becomes clear when we compare Table 1 with Table 6. A typical example is an image showing the erosion of vegetation on the shore after a tsunami (https://www.the-cryosphere.net/10/995/2016/tc-10-995-2016-f07.jpg). The annotators selected one visible term: cliff. The SVM predicted a large number of very concrete terms, that indeed are likely to appear on an image: 'glacier terminus', 'shore', 'port', 'tsunami', 'waves', 'sea level', 'beach', 'lagoon', 'vegetation', 'boat', 'birch', 'bay', 'cliff', 'glacier', 'shores', 'ice'. Only *shores* is here a correct suggestion, that, however, was not selected by the annotators in this case.

We also trained a logistic regression classifier that gave almost the same results as the support vector classifier. In addition now the coefficients learned for each feature (see Table 7) give some additional insight in the usefulness of each feature. The coefficients (though computed only on a small part of the whole dataset) confirm the picture that we already had: For finding visual terms concreteness turns out to be very important. For the key terms the distributional similarity between a keyword and the average of all caption words is the feature with the highest weight. IDF is not important for either of the tasks. Finally, the pattern looking for an explicit phrase *'Picture of ... '* gets a high weight. This is not contradicting the low performance of this feature. If the feature is present, it is a very strong indicator that the following word is depicted, but usually the pattern is not found it gives no information.

[1] Determined using grid search

6 CONCLUSIONS AND FUTURE WORK

We have created a dataset with image-caption pairs extracted from scientific open access publications. All texts and images have a CC-BY or similar liberal copyright and can be reused freely. For each image we extract concepts from the caption and from sentences referring to the image. For each extracted concept two annotators decided whether the concept is visible in the image. The dataset differs from other datasets with images and captions both in the nature of the images and in the type of relation between image and text.

We have shown, that we can predict with a considerable level of accuracy what terms from the text are likely to represent concepts visible in the image without analysing the image. We found that concreteness of words is a key property for this prediction.

The extraction of visual terms and key terms was used to annotate our dataset. Some of the images from the dataset along with the extracted keywords and categories derived from that were uploaded semi-automatically to Wikimedia Commons (https://commons.wikimedia.org/wiki/Category:Uploads_from_NOA_project). Since all terms are titles from Wikipedia articles we can collect the wikipedia categories of these classes. Classes that are covering several keywords and visual terms are very likely to fit well to the image and are proposed as a category when the image was uploaded.

Table 6: Results for the prediction of visible terms. All values are averages with their standard deviations from the extraction for 329 captions (317 for keywords) using 5-fold cross validation.

Method	AUC	Prec	Rec	# of pred.
Vis. terms	0.84 ± 0.17	0.37 ± 0.28	0.80 ± 0.32	7.4 ± 8.6
Key terms	0.80 ± 0.24	0.44 ± 0.32	0.64 ± 0.38	4.4 ± 3.2

Table 7: Coefficients for features in the logistic regression models.

Feature	Vis. Term Coefficient	Keyword Coefficient
idf	0.00 ± 0.00	0.05 ± 0.01
caption similarity	3.75 ± 0.17	4.49 ± 0.18
concreteness	8.63 ± 0.18	0.47 ± 0.07
pattern	3.03 ± 0.67	1.57 ± 0.57
position	0.39 ± 0.03	1.03 ± 0.31

For future work we plan to use contextualised word embeddings as features for the term classification. We expect e.g. that the term *Fish bone* will have different embeddings in the context *Picture of a fish bone* than in the context . . . *extracted from fish bone*. We expect that a classifier can use these differences to distinguish depicted from other concepts.

REFERENCES

Algarabel, S., Ruiz, J. C., and Sanmartin, J. (1988). The University of Valencia's computerized word pool. *Behavior Research Methods, Instruments, & Computers*, 20(4):398–403.

Brysbaert, M., Warriner, A. B., and Kuperman, V. (2014). Concreteness ratings for 40 thousand generally known English word lemmas. *Behavior Research Methods*, 46(3):904–911.

Charbonnier, J. and Wartena, C. (2019). Predicting word concreteness and imagery. In *Proceedings of the 13th International Conference on Computational Semantics - Long Papers*, pages 176–187, Gothenburg, Sweden. Association for Computational Linguistics.

Clark, J. M. and Paivio, A. (2004). Extensions of the Paivio, Yuille, and Madigan (1968) norms. *Behavior Research Methods, Instruments, & Computers*, 36(3):371–383.

Frank, E., Paynter, G. W., Witten, I. H., Gutwin, C., and Nevill-Manning, C. G. (1999). Domain-Specific Keyphrase Extraction. In *Proceedings of the Sixteenth International Joint Conference on Artificial Intelligence*, IJCAI '99, pages 668–673, San Francisco, CA, USA. Morgan Kaufmann Publishers Inc.

Friendly, M., Franklin, P. E., Hoffman, D., and Rubin, D. C. (1982). The Toronto Word Pool: Norms for imagery, concreteness, orthographic variables, and grammatical usage for 1,080 words. *Behavior Research Methods & Instrumentation*, 14(4):375–399.

Gong, Z., Cheang, C. W., et al. (2006). Web image indexing by using associated texts. *Knowledge and information systems*, 10(2):243–264.

Gong, Z. and Liu, Q. (2009). Improving keyword based web image search with visual feature distribution and term expansion. *Knowledge and Information Systems*, 21(1):113–132.

Hessel, J., Mimno, D., and Lee, L. (2018). Quantifying the visual concreteness of words and topics in multimodal datasets. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 2194–2205, New Orleans, Louisiana. Association for Computational Linguistics.

Jeong, J.-W., Wang, X.-J., and Lee, D.-H. (2012). Towards measuring the visualness of a concept. In *Proceedings of the 21st ACM international conference on Information and knowledge management*, pages 2415–2418. ACM.

Kehat, G. and Pustejovsky, J. (2017). Integrating vision and language datasets to measure word concreteness. In *Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*, pages 103–108, Taipei, Taiwan. Asian Federation of Natural Language Processing.

Krippendorff, K. (1970). Estimating the reliability, systematic error and random error of interval data. *Educational and Psychological Measurement*, 30(1):61–70.

Leong, C. W. and Mihalcea, R. (2009). Explorations in automatic image annotation using textual features. In *Proceedings of the Third Linguistic Annotation Workshop (LAW III)*, pages 56–59.

Leong, C. W., Mihalcea, R., and Hassan, S. (2010). Text mining for automatic image tagging. In *Coling 2010: Posters*, pages 647–655.

Lin, T.-Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., Dollár, P., and Zitnick, C. L. (2014). Microsoft coco: Common objects in context. In *European conference on computer vision*, pages 740–755. Springer.

Martinec, R. and Salway, A. (2005). A system for image–text relations in new (and old) media. *Visual communication*, 4(3):337–371.

Mikolov, T., Sutskever, I., Chen, K., Corrado, G., and Dean, J. (2013). Distributed representations of words and phrases and their compositionality. In *Proceedings of the 26th International Conference on Neural Information Processing Systems - Volume 2*, NIPS'13, pages 3111–3119, USA. Curran Associates Inc.

Otto, C., Springstein, M., Anand, A., and Ewerth, R. (2019). Understanding, categorizing and predicting semantic image-text relations. In *Proceedings of the 2019 on International Conference on Multimedia Retrieval*, ICMR '19, pages 168–176, New York, NY, USA. ACM.

Paivio, A., Yuille, J. C., and Madigan, S. A. (1968). Concreteness, imagery, and meaningfulness values for 925 nouns. *Journal of Experimental Psychology*, 76(1, Pt.2):1–25.

Salton, G., Yang, C.-S., and Yu, C. T. (1975). A theory of term importance in automatic text analysis. *Journal of the American society for Information Science*, 26(1):33–44.

Sohmen, L., Charbonnier, J., Blümel, I., Wartena, C., and Heller, L. (2018). Figures in scientific open access publications. In Méndez, E., Crestani, F., Ribeiro, C., David, G., and Lopes, J. C., editors, *Digital Libraries for Open Knowledge*, pages 220–226, Cham. Springer International Publishing.

Srihari, R. K., Zhang, Z., and Rao, A. (2000). Intelligent indexing and semantic retrieval of multimodal documents. *Information Retrieval*, 2(2):245–275.

Turney, P. D. (2000). Learning Algorithms for Keyphrase Extraction. *Inf. Retr.*, 2(4):303–336.

Unsworth, L. (2007). Image/text relations and intersemiosis: Towards multimodal text description for multiliteracies education. In *Proceedings of the 33rd IFSC: International Systemic Functional Congress*. Pontifícia Universidade Católica de São Paulo.

Zhao, Z.-Q., Zheng, P., Xu, S.-t., and Wu, X. (2019). Object detection with deep learning: A review. *IEEE transactions on neural networks and learning systems*.