

Automatically Selecting Images for News Articles with Keyword Extraction



SYSTEM OVERVIEW

- An **Article Preprocessor** turns the plain text of a news article into a list of terms. Each term is described by certain features.

 "eirmod" =>
 - Using these features, two different **ranking mechanisms** predict how relevant each term is for the image search.
 - The most relevant terms are composed into a query string.
 - This string is used to query an image database.

Lorem ipsum dolor sit fo: 0.01 p: 0.7569 amet, consetetur "ipsum dolor" => "voluptua" => sadipscing elitr, sed diam tf: 4, tf: 7, nonumy eirmod tempor fo: 0.21, fo: 0.24, "eirmod magna aliquyam" invidunt ut labore ec: "Event" p: 0.2319 Terms **Article** Query Term Query ___ Image Article Terms + Features Preprocessor + Features Text Generation Search + Predictions

tf: 18, fo: 0.01,

p: 0.9643

fo: 0.12,

tf: 5,

"magna aliquyam" =>

ec: "Location",

ec: "HumanProtagonist",

Fig. 1: Overview of the image selection pipeline

A. With pre-trained Machine Learning Models

"lorem" =>

tf: 3,

fo: 0.01,

"lorem ipsum" =>

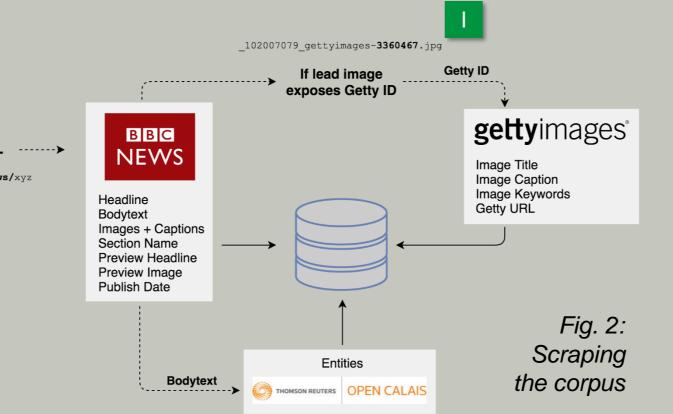
tf: 1,

ec: "Product"

What is a good image search term and what is not? There is no real-world evidence for this, therefore training data had to be assembled from existing information.

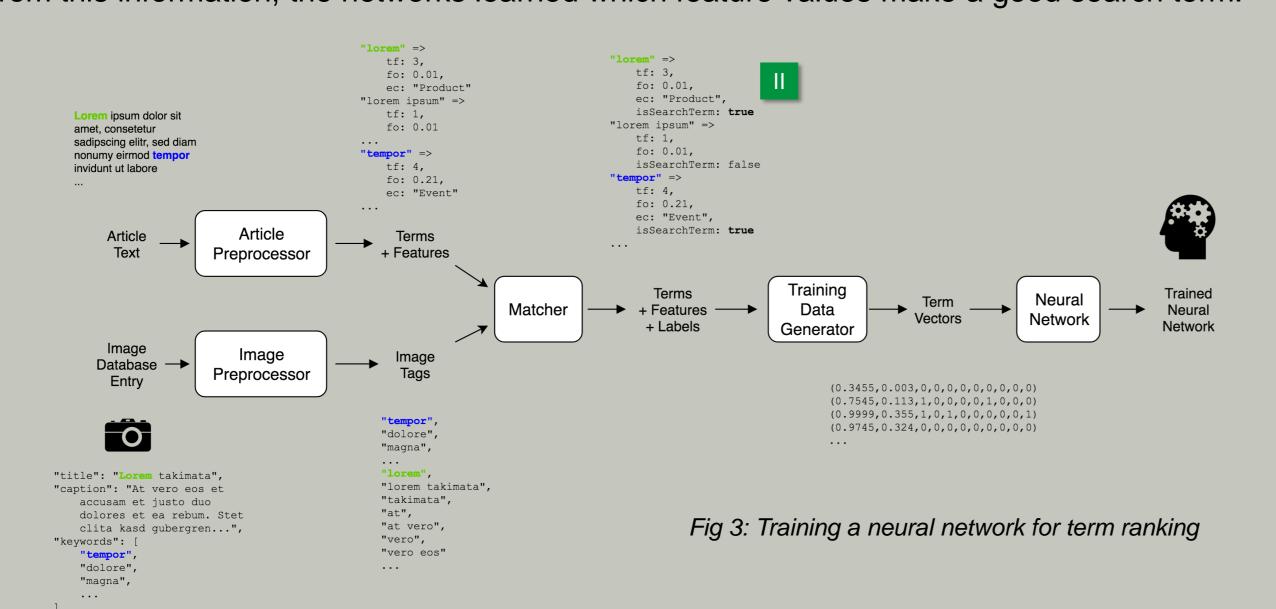
http://www.bbc.com/news/xyz

When **BBC News** uses photos by **Getty Images**, they sometimes expose the image's ID. I Exploiting this, we downloaded >1500 articles along with image meta data from the Getty database. (see Fig. 2)



Assuming that each term in the image meta data suffices as a query to find exactly that image, we generated our training data. Article terms were matched with the image descriptions: Each term that occured both in the article and in the image was labelled as search term.

From this information, the networks learned which feature values make a good search term.



B. With simple Statistics

Assuming that the most relevant terms occur often and early, their relevance is calculated as follows:

$$p(tf, fo) = \frac{tf}{\max(TF)} * (1 - fo)$$

where *tf* denotes the frequency of a term, *fo* its first occurrence value and max(TF) the highest frequency value of all terms in the article.

Features of a Term

Time waits for no man. Unless that man is Chuck Norris.

Term frequency (tf) is the number of times a term occurs in an article.

tf("man") = 2

First occurrence (fo) is the relative position in an article at which a term occurs for the first time – with 0 representing the very first character of the article and 1 the last.

fo(,,man'') = 0.3273

Entity category (ec) is a nominal value describing some specific groups of terms, such as "Event", "HumanProtagonist" or "Location".

ec("Chuck Norris") = HumanProtagonist

PERFORMANCE

Machine Learning vs. Statistics

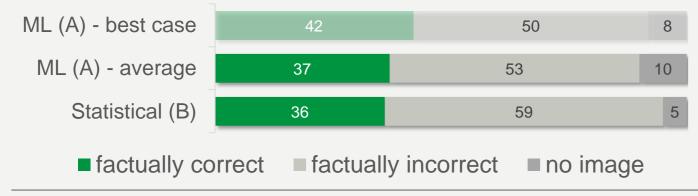


Fig. 4: Average performance of approaches A and B, including the best performing run for comparison

Evaluation methodology

- Sample of 100 BBC articles
- For each article, image selection was run with 4 neural networks + the statistical approach
- Selected images were classified manually as "factually correct" or "factually incorrect", according to our own definition of factual correctness

- The two approaches only differ slightly in their average performance. However, one neural network stood out and selected correct images for 42 percent of all articles.
- Adding the *first occurrence* feature to the neural networks increased the number of correct images by almost 10. In turn, adding *entity category* actually deteriorated the results by almost 4 correct images. *Term frequency* hardly had any impact at all.
- The Machine Learning approach (A) excelled on articles with special interest topics such as "Entertainment & Arts" or "Business". The more regional the article's scope got, the more did the system's performance decrease except for the Statistical approach (B) that outperformed the neural networks on regional news.

Term Frequency 0,33 First Occurrence 9,66 Entity Category -3,66

Fig. 5: Change in the number of correct images that resulted from adding one specific feature to the neural networks

Performance per Article Topic

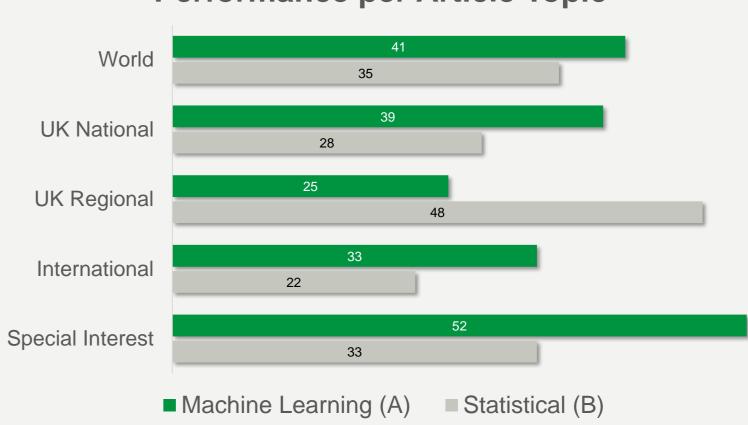


Fig. 6: Number of correct images, by article topic and term ranking approach