# ANALYSING AND PREDICTING SENTIMENT OF IMAGES ON THE SOCIAL WEB

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#### INTRODUCTION

Images often illicit emotion or sentiment. Can a machine learn what kinds of visual features might lead to a positive or negative sentiment? In this study we have created a large collection of images which have been selected such that they are likely to have positive or negative sentiment associations. These images

have been automatically assigned sentiment scores based upon their textual metadata. Experiments have then been performed to investigate whether low-level image features correlate with the sentiment scores. In addition we have applied information theoretic approaches to determine which specific visual features are the most discriminative.

#### THE IMAGE DATASET

The top-1000 most **positive** and top-1000 most **negative** words from **SentiWordNet** were selected to form query terms for images that were likely to be associated with either positive or negative sentiment.



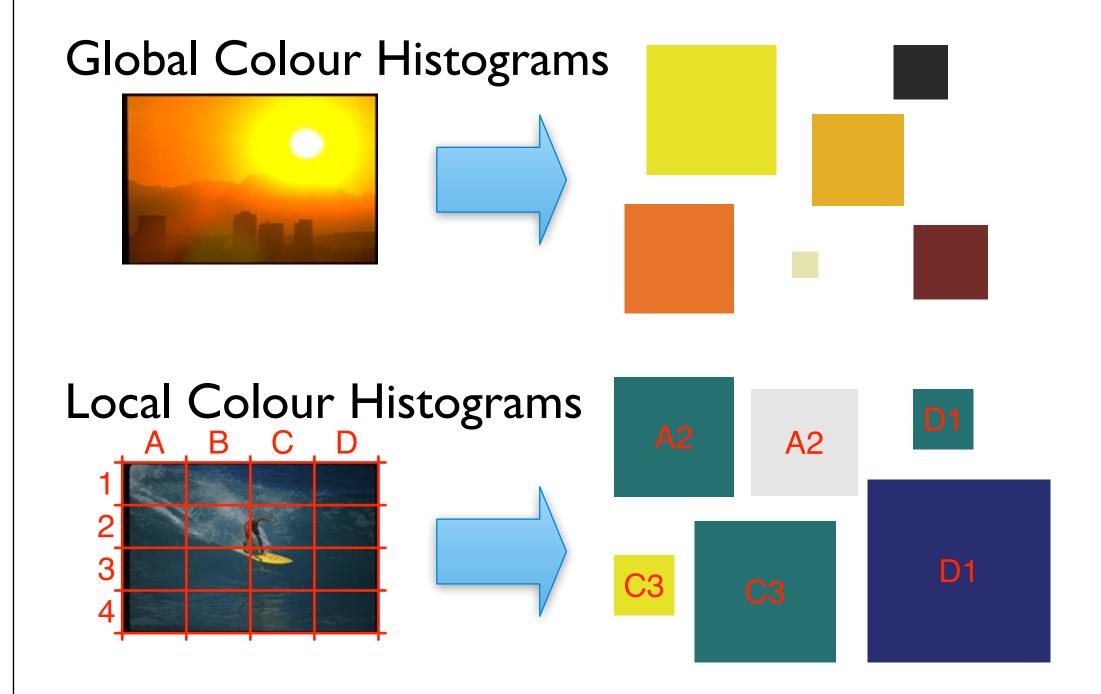
law-of-effect who better-offwonderful delightful well-to-do be on heaven-sent heaven-sent in the intritious ness intritious ness in the intritious ness in the intritious ness in the intritious ness in the intritious ness intrit

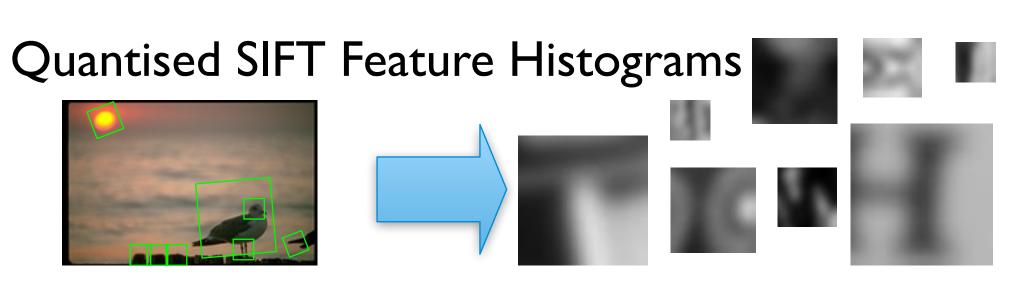
Up to 5000 images per term were selected by searching **Flickr** with each query term. Over **586000** images were collected together with their respective metadata.



#### VISUAL FEATURES

Image content was modelled as a 'bag of visual terms'. Three different types of feature were chosen for this study.





### ASSIGNING SENTIMENT TO THE IMAGE DATASET

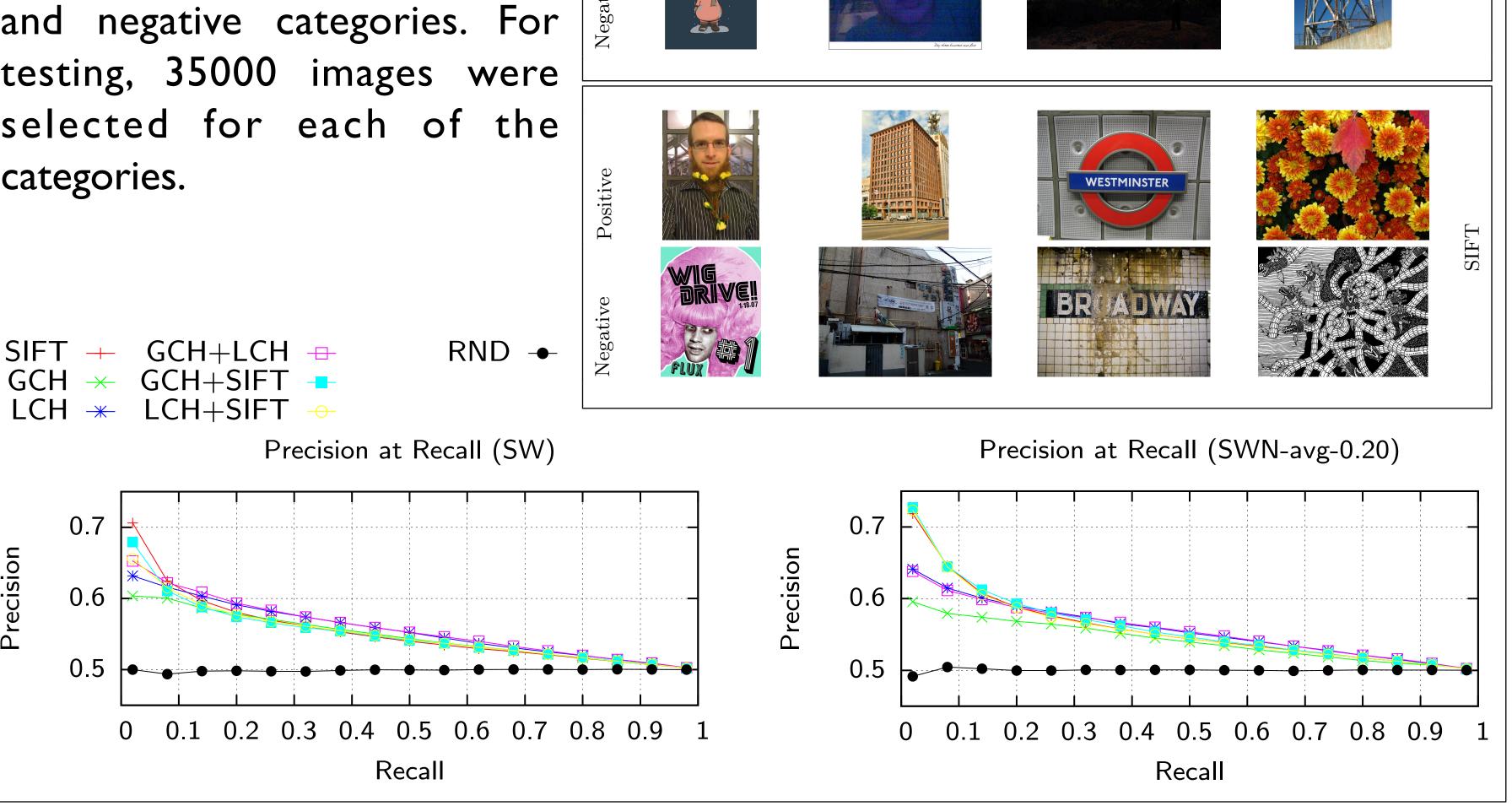
Sentiment scores were assigned to the images in three different ways; in the first (SW) images were assigned either positive (+1) or negative (-1) sentiment scores if the metadata only contained positive or negative terms (images were rejected for the other cases). In the second case (SWN-avg-T) we filtered the metadata by removing all terms corresponding to synsets with a sentiment (positive or negative) less than T and then averaged the sentiment scores across the remaining terms. Thirdly, for cross-checking our results, we uniformly randomly assigned scores to each image in the range -1 to 1.

7		positive	negative	labeled
<b>)</b>	SW	294,559	199,370	493,929
•	SWN-avg-0.00	316,089	$238,\!388$	$554,\!477$
ı	SWN-avg-0.10	$260,\!225$	190,012	$450,\!237$
^	SWN-avg-0.20	194,700	149,096	343,796
	RND	293,456	292,812	$586,\!268$

## CLASSIFICATION EXPERIMENTS

We performed a series of binary classification experiments in order to assess the potential of using the visual features for predicting sentiment polarity.

Features from 100000 randomly selected images were used for training a linear SVM, with an equal split between the positive and negative categories. For testing, 35000 images were selected for each of the categories.



## SENTIMENT CORRELATED FEATURES

Mutual information was used to investigate which visual features most strongly corresponded with positive and negative sentiments. The most discriminative visual features are visualised here.

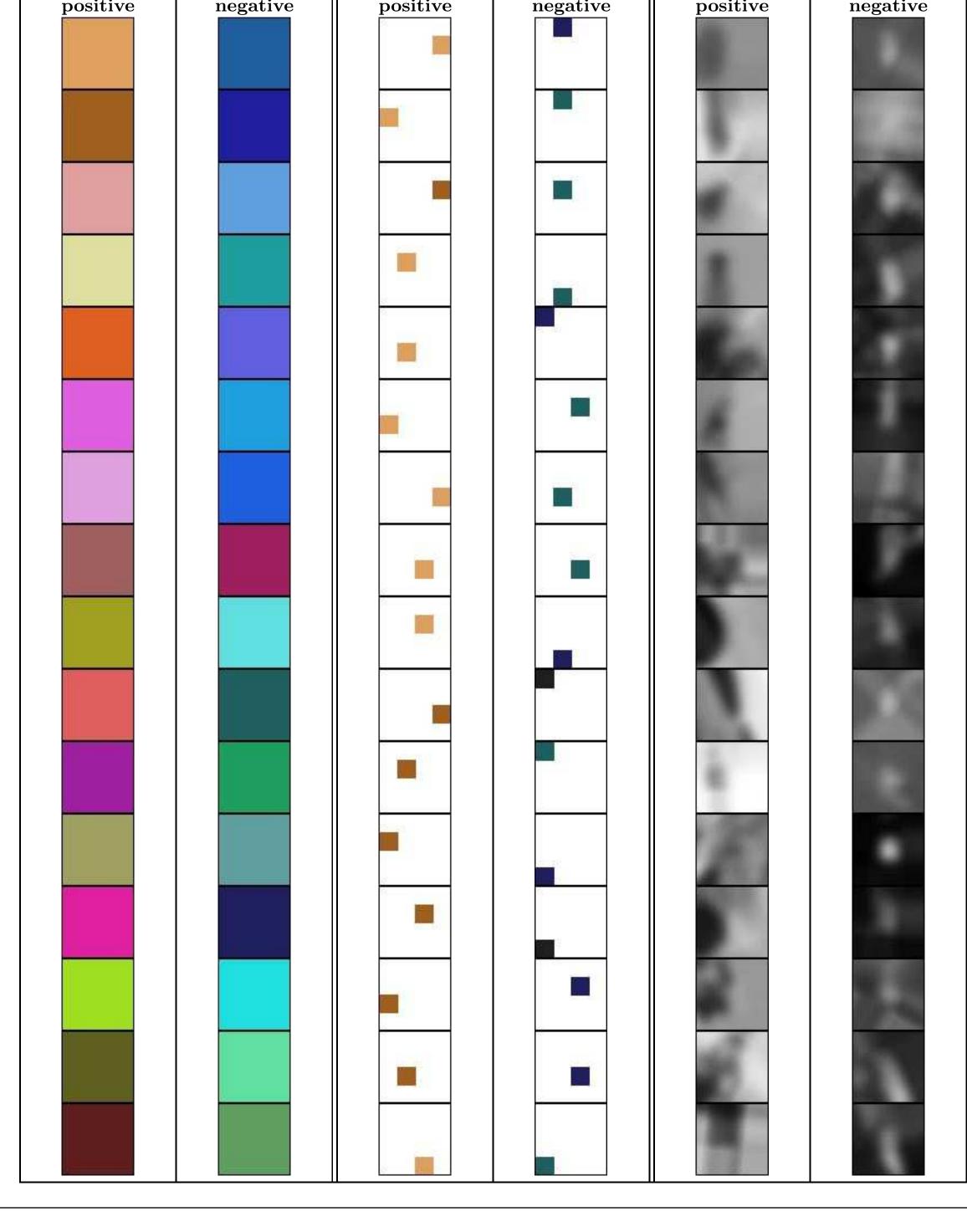
Global Colour Histogram

Local Colour Histogram

SIET Visual Torms

Interestingly, the visualisation of the strongest colour features suggests skin and earthy tones correspond to positive sentiment, whilst blue-tones tend to correlate with negative sentiment. This correlation is especially interesting as it mirrors human perception of warm (positive) and cold (negative) colours.

An interpretation of the most discriminant SIFT patches is more difficult to formulate, however, it is apparent that the top features for each class are visually similar to each other.



#### CONCLUSIONS

The SIFT-based feature, and the SIFT-based feature combined with the global colour histogram provided the best performance in our experiments. The performance attained shows that the selected visual features can to a certain degree help predict the polarity of sentiment. However, there is much room for improvement possibly through the selection of better features and more advanced classifiers.







