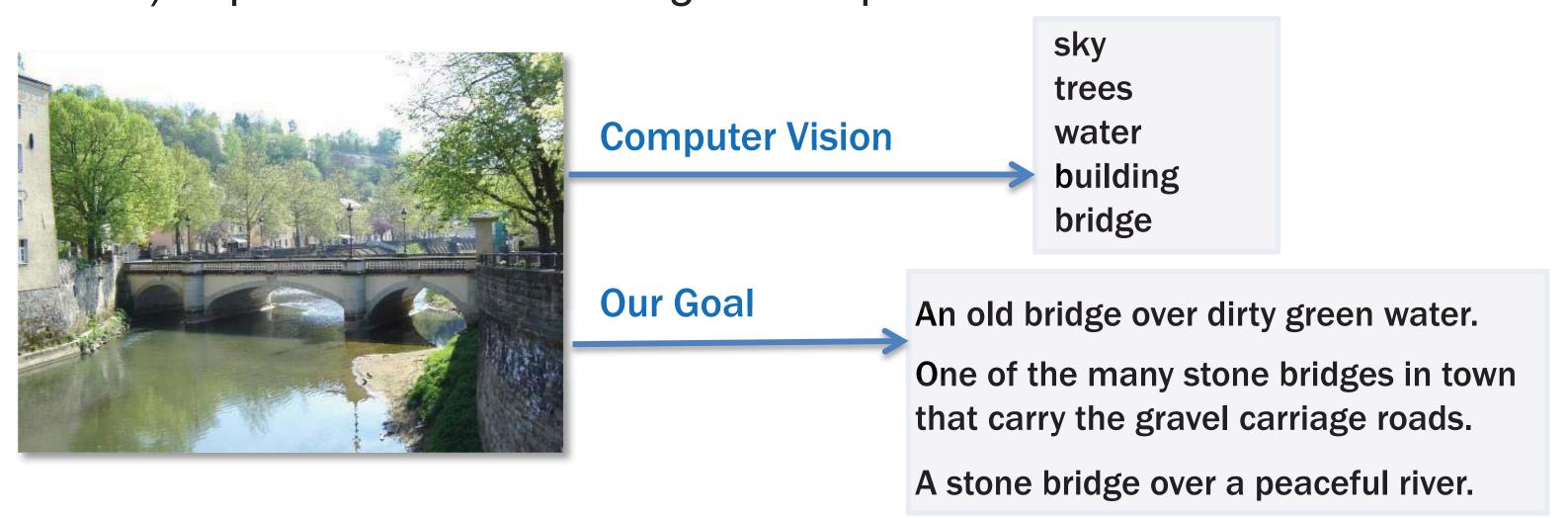


# Im2Text: Describing Images Using 1 Million Captioned Photographs

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#### Contributions

- SBU Captioned Photo Dataset: A large novel data set containing 1 million images from the web with associated captions written by people, filtered so that the descriptions are likely to refer to visual content. [http://tamaraberg.com/sbucaptions]
- A description generation method that utilizes global image representations to retrieve and transfer captions from our data set to a query image.
- A description generation method that utilizes both global representations and direct estimates of image content (objects, actions, stuff, attributes, and scenes) to produce relevant image descriptions.



#### **SBU Captioned Photo Dataset**



Little girl and her dog in the sand on Waitarere beach. northern Thailand. They both seemed interested in what



Our dog Zoe in her bed.

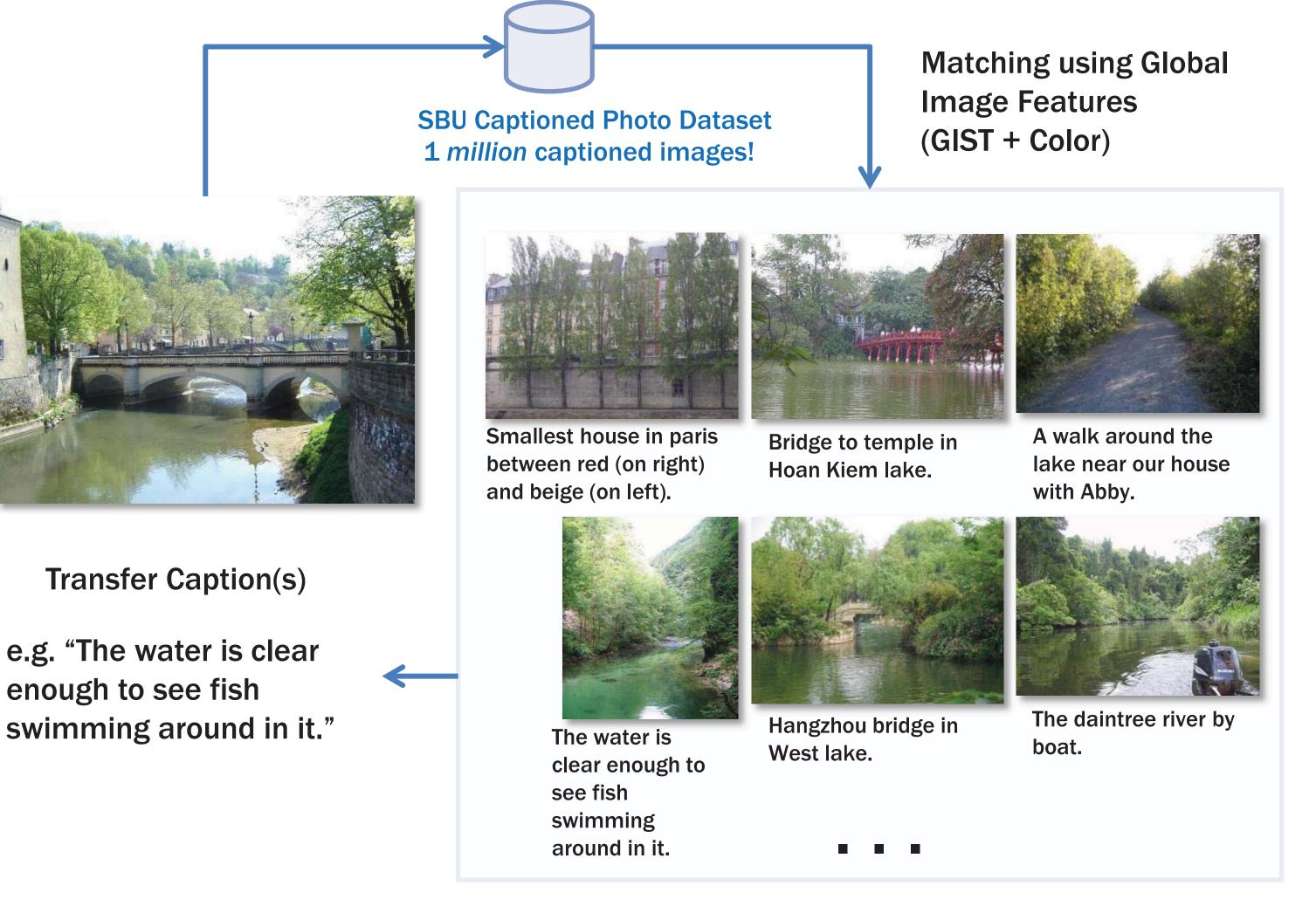


Interior design of modern white and brown living room furniture against white wall with a lamp hanging.

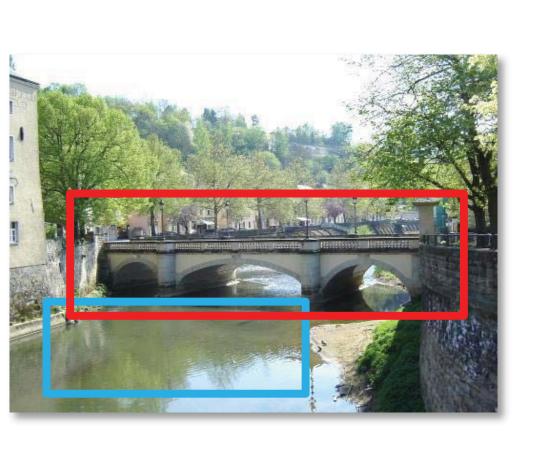


Emma in her hat looking super cute.





Rerank retrieved images using high level content (captions, object detections, scene classification, stuff detections, people & actions)



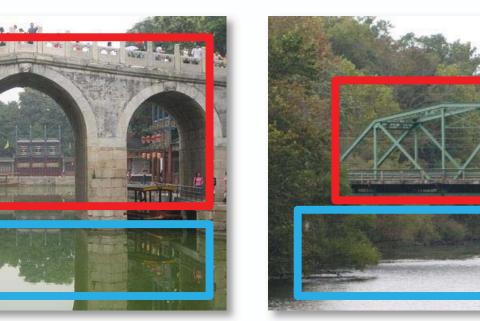
The Egyptian cat statue by the

machine in the pantheon.

floor clock and perpetual motion

**Transfer Caption(s)** 





The **bridge** over the Iron bridge over the Duck river.



Bridge over Cacapon river. The Daintree river by boat.

#### High level information

Objects: 80 object categories using part-based deformable models and compute distances with objects detected in the query image based on visual attributes and raw visual descriptors.

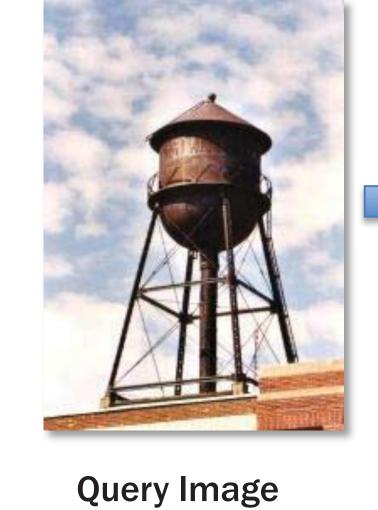
People/Actions: Detect people and pose using state-of-the-art methods and compute person similarity using an attribute based representation of pose.

Stuff: Detect stuff regions using a sliding window SVM scoring function with texton, color and geometric features as input. We determine similarity with the query image using product of SVM probabilities. (water, etc)

Scenes: Train classifiers using global features for 26 common scene types and use the vector of classifier responses as a feature to compute similarity between images.

**TFIDF:** Rank the words in the returned set of image captions using their term-frequency inverse document frequency scores and follow a similar approach with the keywords for each object detection in the matching image set. As a result we obtain text-based TFIDF scores and object-detection-based TFIDF scores.

#### **Dataset size**





while walking along the beach in Ocracoke, NC



This is a boat I saw while walking near the house we rented.



1,000



Granite in green

Oil Co. sign in Green River, Utah. 10,000



still see the RCA dog in the stained glass window



handle.





The famous Liver bird atop the Royal Liverpool Insurance building near the calais beach in newly tarted up docks. France. 100,000

tower in Sidney,





Old cone water tower with Graffit in Detroit Michigan



Past work on image retrieval has shown that small collections often produce spurious matches. Increasing data set size has a significant effect on the quality of retrieved global matches. Quantitative results also reflect this (see table at the bottom)

### **Good results**



**Amazing colours in** the sky at sunset with the orange of the cloud and the blue of the sky behind.



at Luukki Espoo



Fresh fruit and vegetables at the market in Port Louis Mauritius.



Tree with red leaves in the field in autumn.



One monkey on the tree in the **Ourika Valley Morocco** 



My house...yeah right. This

was the beach house we

stayed in with my family for

vacation, in the Outer Banks.

**Clock tower** against the sky.



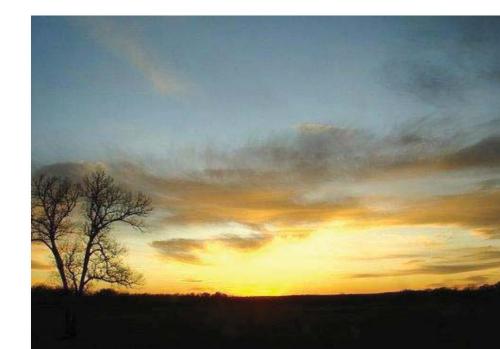
Reflection of the clear blue sky in the water.



Strange cloud formation literally flowing through the sky like a river in relation to the other clouds out there.



The sun was coming through the trees while I was sitting in my chair by the river



Under the sky of burning clouds.

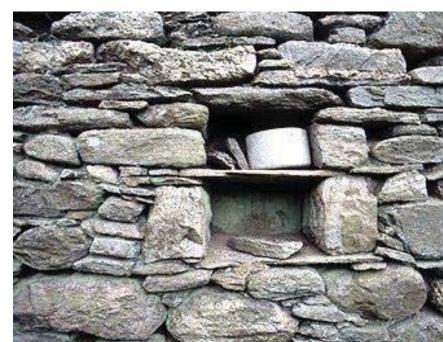


**Stained glass** window in Eusebius church.

**Incorrect context** 



From the big tower on the hill over looking central Wakkanai.



**Completely wrong** 

An old roman wall by the tower of London.

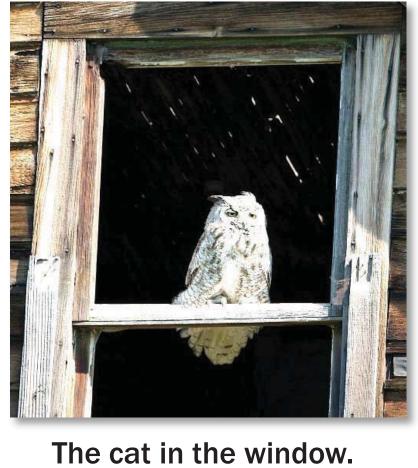


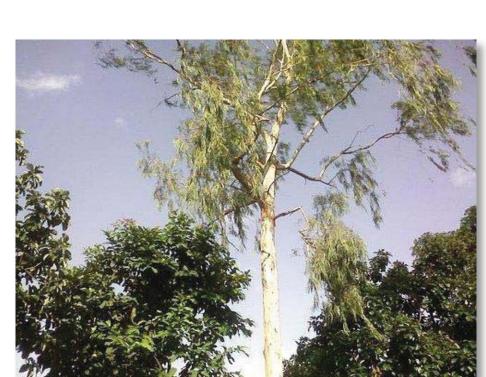
A tree right around the corner from our house is this tree after the snow fell it was so beautiful.

# **Bad results**

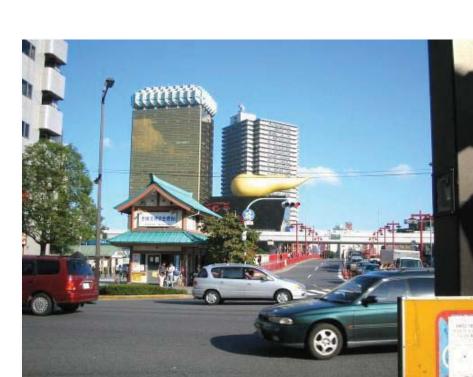


Kentucky cows in a field.





Tree beside the river.



The sky is blue over the Gherkin.

The boat ended up a kilometre from the water in the middle of the airstrip.



Water over the road.

## BLEU score evaluation

DLLO 30010 CValuation	
Method	BLEU score
Global matching (1k)	0.0774 +- 0.0059
Global matching (10k)	0.0909 +- 0.0070
Global matching (100k)	0.0917 +- 0.0101
Global matching (1million)	0.1177 +- 0.0099
Global + Content matching (linear regression)	0.1215 +- 0.0071
Global + Content matching (linear SVM)	0.1259 +- 0.0060

### **Human evaluation**

In addition, we propose a new evaluation task where a user is presented with two photographs and one caption. The user must assign the caption to the most relevant image. For evaluation we use a query image, a random image and a generated caption.

Caption used	Success rate
Original human caption	96.0%
Top caption	66.7%
Best from our top 4 captions	92.7%

Please choose the image that better corresponds to the given caption:





