Proposal

Executive Summary

Image captioning of earth observation imagery: this is our joint capstone project in coalition with MDA. By Dora Qian, Fanli Zhou, James Huang, and Mike Chen. Special thanks to our mentor Varada, and our partners at MDA: Shun, and André.

In this project, we aim to create a novel tool that generates captions for overhead satellite image, and manages and updates a database of these images.

Introduction

MDA is a Canadian aerospace company, manufacturing equipment for space applications, specializing in space surveillance, space robotics, and satellite systems. MDA has access to a vast database of the aforementioned satellite images. These uncaptioned photos without context do not offer very much information on their own, and are difficult and costly to work with, as people naturally query things with words. By extracting a caption from an image, it becomes much easier to work with in analysis. These captions can allow images to be easily tagged and sorted, they can be used in a search query, used to evaluate image similarity, and other downstream applications in machine learning, such as natural language processing. In doing so, we will face challenges, as most image models currently available are trained on traditional ImageNet type images, due to the fundamentally differing nature of satellite images, knowledge transfer will be less effective as we are working on a different domain. MDA currently has no existing solution to this problem, so our work will be novel to the company. To break the problem down, we will be working with other, captioned datasets first. We will clean and organize the data into a database, and run the initial training and validation process on that data. We have access to several different datasets, and those will be used to test cross dataset performance. Once we're satisfied with the performance on the captioned datasets, we'll manually evaluate the performance on the MDA dataset by using the model to generate captions, and then score those captions by hand.

Final Data Product Description

The final data product is a complete image captioning pipeline consisting of three independent modules: a database, a deep learning model and an interactive visualization and database updating tool.

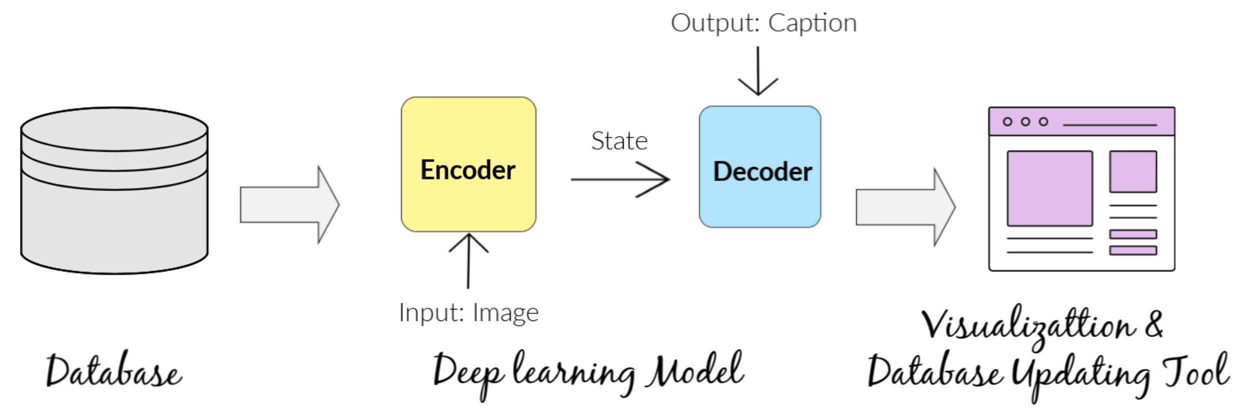

Figure 1. Final data product

First, the non-relational database will be used to store all the remote sensing images, associated captions and evaluation scores. We will start by creating three separate folders storing these data for ease of extraction. Both the human-annotated and machine-generated data will be stored in this database.

Second, the deep learning model will be capapble of loading data from the database, as well as train and predict on data. The model will be designed to be easy to maintain and update. PyTorch would be used for modelling and AWS P2 or P3 instances would be used for cloud computing.

Lastly, a Dash-based visualization would allow users to get predicted captions from the model and update new image-caption pairs in the database. Users would have two options, either to select one or multiple images from the database or upload any new ones outside the database. The images, machine-generated captions, human-annotated captions and scores would be displayed as results.

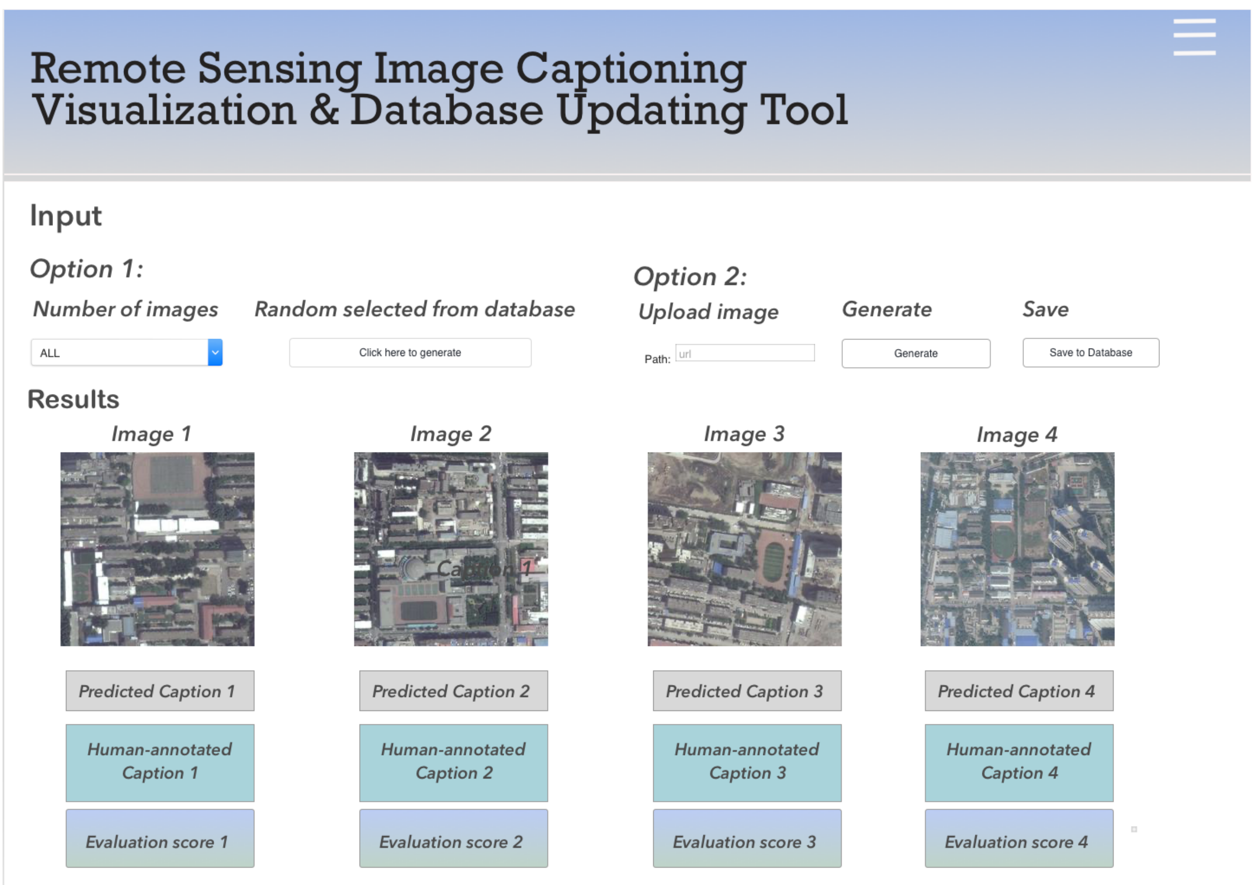

Figure 2. Visualization and database updating tool

Data Description

In order to train our model, we have three labeled datasets: UCM_captions, RSICD and Sydney_captions.

The UCM_captions dataset is based off of the "University of California Merced's Land Use Dataset". It contains land-uses satellite images. There are 21 different classes of images ranging from airplane fields, baseball diamond, overpass, runways and many more. There are 100 images in every class, and each image has a resolution of 256 X 256 pixels. (2100 images)

The Sydney_captions dataset is extracted from a large 18000 X 14000 pixel image of Sydney taken from Google Earth. Each of the images in the dataset are selected and cropped from the original much larger Google Earth image. There are 7 different classes of images in this dataset, comprised of residential, airport, river, oceans, meadow, industrial and runway images. Each image has a resolution of 500 X 500 pixels. (613 images)

The RSICD dataset (Remote Sensing Imaging Captioning Dataset) is the state of the art dataset, which contains images captured from airplanes and satellites. The captions are sourced from volunteers, and every image will include 5 different captions, from 5 different volunteers to ensure diversity of the caption. Each image has a resolution of 224 X 224 pixels. (10,922 images)

Each of the datasets contain different image file types and images sizes. In order to apply our data science techniques, we must first standardize all images across all three datasets.

Data Science Techniques Description

We will combine all three datasets and the combined dataset into training (64%), validation (16%), and test (20%) datasets. Sticking to the golden rule, we will train and tune models with the training and validation datasets only. We decided to focus on the encoder-decoder model as it's the most common method for image captioning. Here are the three encoder-decoder models we will try:

1. Our first model will be a basic encoder-decoder (CNN + LSTM) model (Fig. 3). We'll first use transferring learning to train this model. We've trained a baseline model with `InceptionV3` for CNN and `Glove` for word embedding using only 800 training examples (source code, written in `TensorFlow`). Fig. 3C shows a good caption and 2D shows a bad caption generated by the model. We see that the baseline model does not do well on some images. The problem could be that unlike natural ImageNet type images, satellite images have a top-down view with many components, and require detailed captions. The model will need to be modified to reflect this.

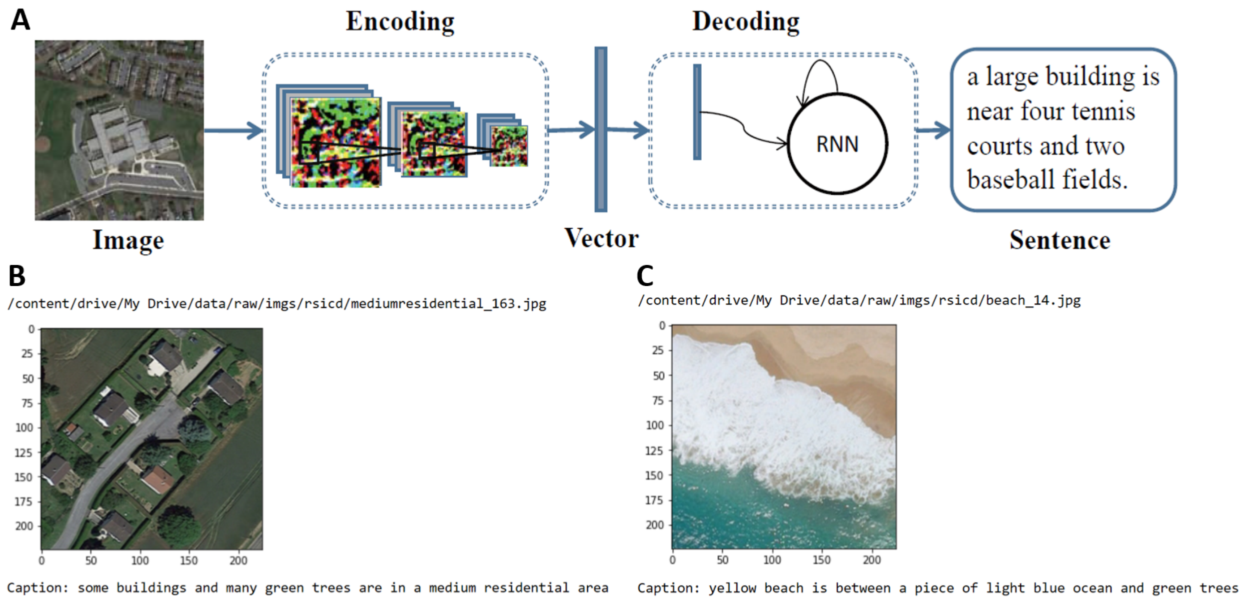

Figure 3. The baseline model architecture and example outputs. A is adapted from (Lu et al. 2018).

2. The second model will have an attention structure on top of the baseline model (Fig. 4). The attention structure takes image features from the CNN convolutional layer and assigns weights to those features. Overall, it could act as moving the focus across the image so that the model can capture more detail and produce a better caption (Xu et al. 2015; Zhang 2019). We will try this architecture and would expect this model to produce more detailed captions compared to the baseline.

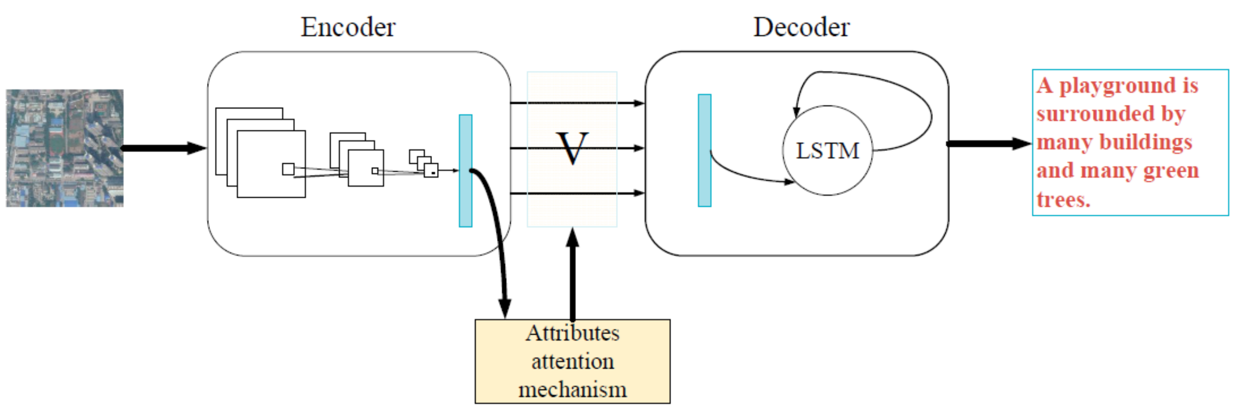

Figure 4. The second model architecture (adapted from (Zhang 2019)).

3. As an extension of the second model, the third model will contain three attention structures on top of the baseline model (Fig. 5). This multi-level attention model better mimics human attention mechanisms and act as moving the focus between the image and the word context to help generate better captions (Li 2020). We are going to implement this architecture and expect this model to produce captions of the best quality.

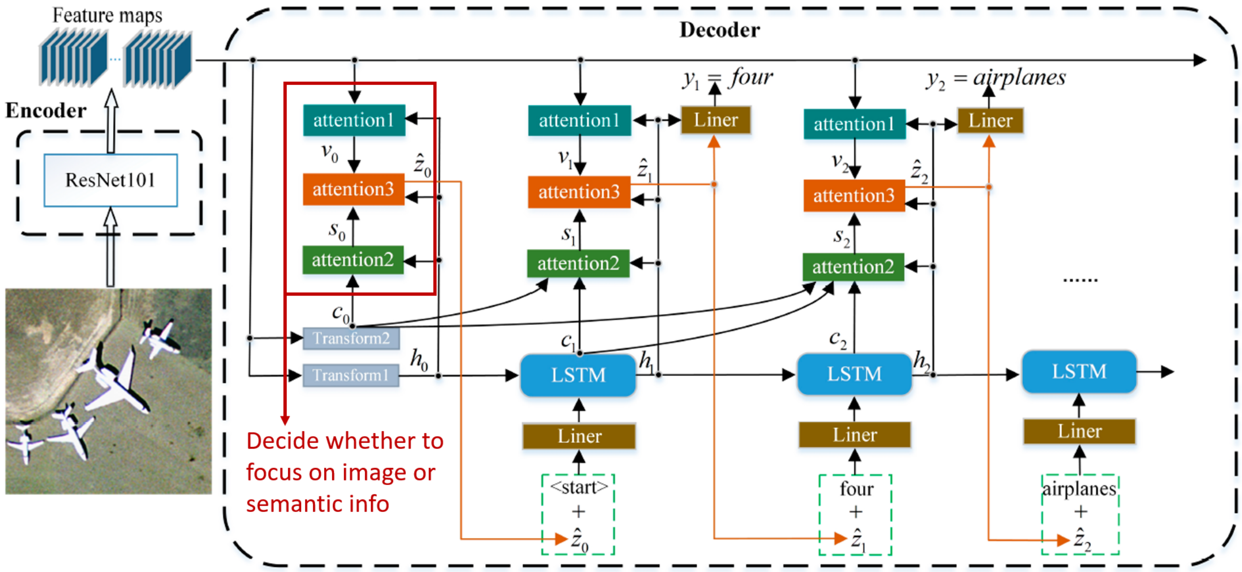

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Figure 5. The third model architecture (adapted from (Li 2020)).

If time permits, we could explore other model architectures and try fine-tuning pre-trained cross-modal models. To assess these models, we can use evaluation metrics suggested in this paper (Li 2020), including BLEU, Meteor, ROUGE_L, CIDEr, and SPICE. Finally, we will test our best model with the test dataset and evaluate the results.

Timeline and Evaluation:

The length of our capstone project is two months, starting from May 4th, 2020 to June 30th, 2020. During these eight weeks, the following five milestones are expected to be achieved: proposal, EDA and database design, model development, visualization tool design and polish. The first two weeks were used for the proposal: we have delivered both a presentation and a written report. Meanwhile, we will start exploratory data analysis, data pre-processing, and database design. The next four weeks will be used for data product development. The three intermediate stages would be run in parallel during this period. Both the database and tool design will take about two weeks while the deep model development will run for four weeks. Three milestones will be achieved by the end of this data product development stage. The last two weeks will be used to improve and polish the final product based on feedback from our mentor, and our partners. We will deliver the final presentation, final written report and final data products to both our MDS mentor and our MDA partners by June 29th, 2020.

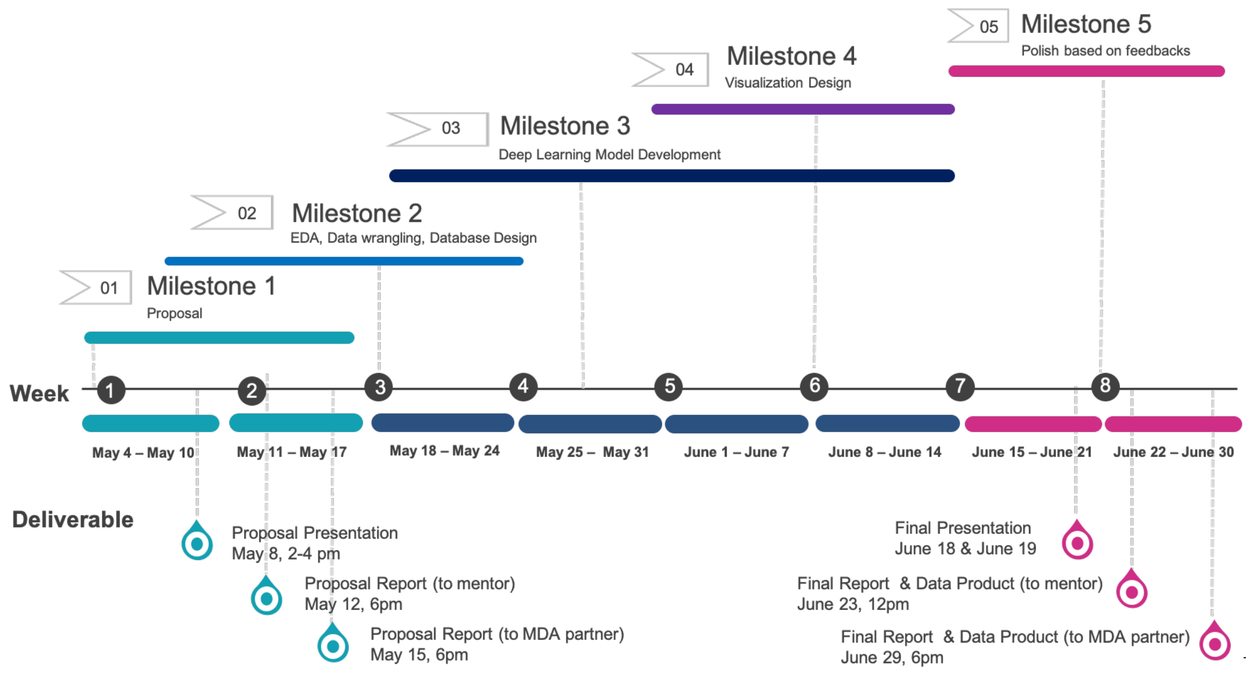

Figure 6. Project timeline

Reference

Li, S.; Jiao, Y.; Fang. 2020. "A Multi-Level Attention Model for Remote Sensing Image Captions." *Remote Sens.* 12 (6): 939. https://doi.org/10.3390/rs12060939.

Lu, Xiaoqiang, Binqiang Wang, Xiangtao Zheng, and Xuelong Li. 2018. "Exploring Models and Data for Remote Sensing Image Caption Generation." *IEEE Transactions on Geoscience and Remote Sensing* 56 (4): 2183–95. https://doi.org/10.1109/tgrs.2017.2776321.

Xu, Kelvin, Jimmy Ba, Ryan Kiros, Kyunghyun Cho, Aaron Courville, Ruslan Salakhutdinov, Richard Zemel, and Yoshua Bengio. 2015. "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention." http://arxiv.org/abs/1502.03044.

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