**CarND-Vehicle-Detection WriteUp**

**You can use this file as a template for your writeup if you want to submit it as a markdown file, but feel free to use some other method and submit a pdf if you prefer.**

**Vehicle Detection Project**

The goals / steps of this project are the following:

* Perform a Histogram of Oriented Gradients (HOG) feature extraction on a labeled training set of images and train a classifier Linear SVM classifier
* Optionally, you can also apply a color transform and append binned color features, as well as histograms of color, to your HOG feature vector.
* Note: for those first two steps don't forget to normalize your features and randomize a selection for training and testing.
* Implement a sliding-window technique and use your trained classifier to search for vehicles in images.
* Run your pipeline on a video stream (start with the test\_video.mp4 and later implement on full project\_video.mp4) and create a heat map of recurring detections frame by frame to reject outliers and follow detected vehicles.
* Estimate a bounding box for vehicles detected.

[**Rubric**](https://review.udacity.com/#!/rubrics/513/view)**Points**

**Here I will consider the rubric points individually and describe how I addressed each point in my implementation.**

**Writeup / README**

**1. Provide a Writeup / README that includes all the rubric points and how you addressed each one. You can submit your writeup as markdown or pdf.**[**Here**](https://github.com/udacity/CarND-Vehicle-Detection/blob/master/writeup_template.md)**is a template writeup for this project you can use as a guide and a starting point.**

You're reading it!

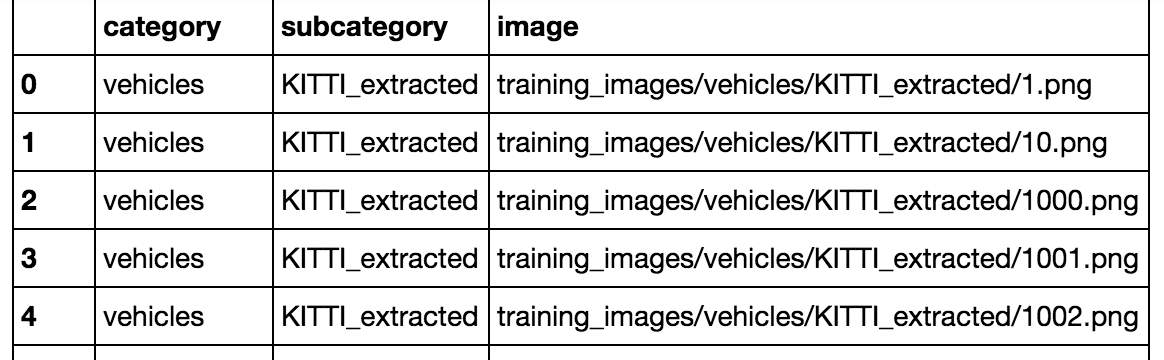
**Histogram of Oriented Gradients (HOG)**

**1. Explain how (and identify where in your code) you extracted HOG features from the training images.**

I would like to introduce the two-part process of developing this solution: the exploratory data analysis, followed by the building of the model and video processing pipeline.

Please note that in the process of building the model, code refactoring may have left the exploratory section in the Jupyter notebooks (namely explore.ipynb) unrunnable, so I will reference its usage in both exploration and the final model.

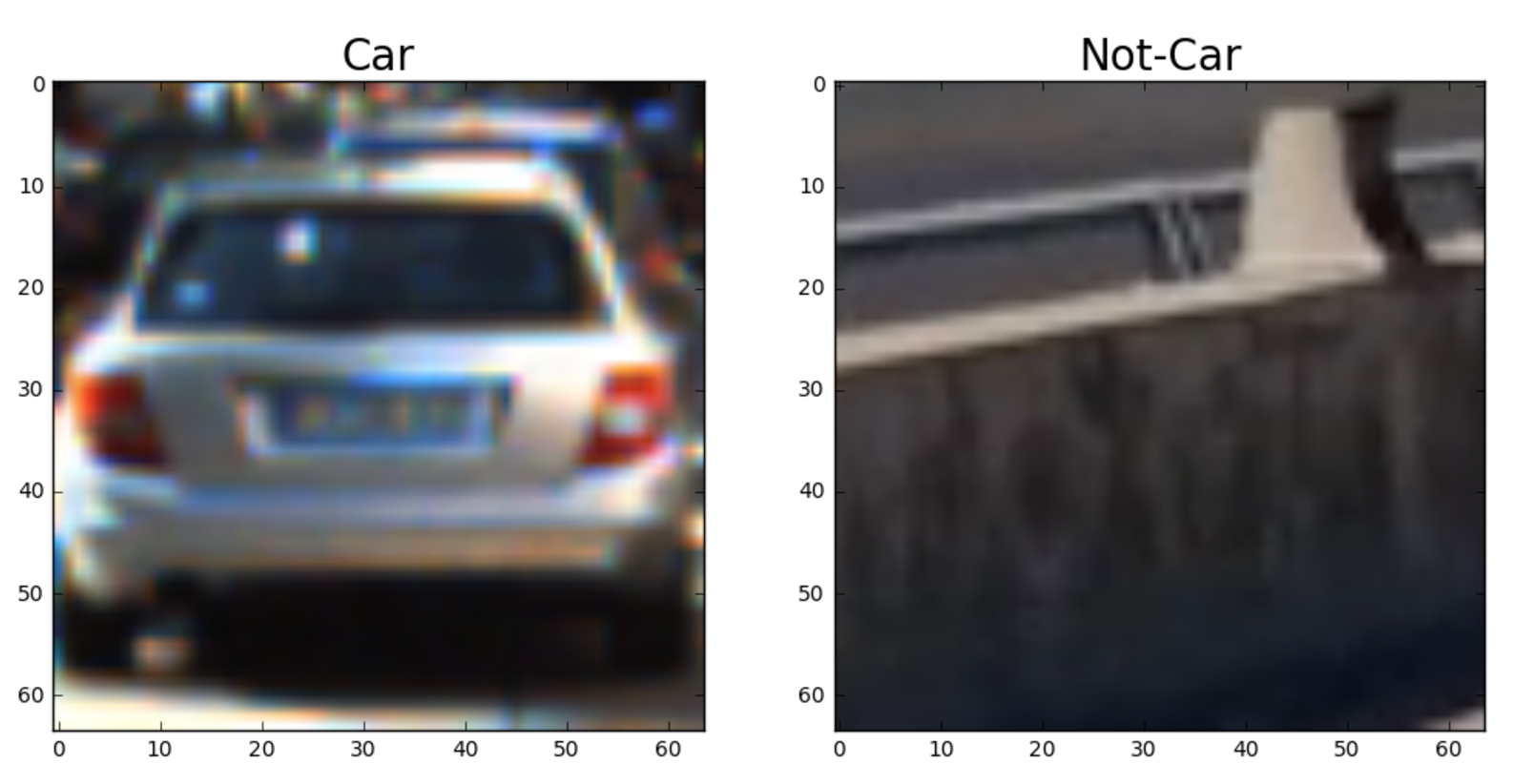
In the exploratory analysis, the section “HOG Feature hyper-parameter training” of explore.ipynb, hyperparameter exploration was conducted with prediction validation performed over a linear SVC model. The next section describes this in more detail. In preparation for this hyper-parameter tuning, a Pandas Data Frame was read in with the columns “category”, “subcategory” and “image”, as such:



This data was shuffled and split into ‘train’ and ‘test’ (i.e. validation) sets. Furthermore, in order to reduce validation set correlation error, the data was further filtered into only using the KITTI\_extracted subcategory data because the other data sets had unlabeled time lapse information. Manual splitting of the validation/training data could have been performed such that similar images do not end up in both training/validation sets, but in the interest of time this was not done.

For training the video processing pipeline, all the data was used and includes the extraction of binned color and histogram features – this can be seen at model.py:#train\_model (around line 14).

The purpose of building the model was to predict the presence of vehicles on the road – an image classification problem. The category labels vehicle and non-vehicle. Here is an example of one of each of the vehicle and non-vehicle classes:

[](https://github.com/udacity/CarND-Vehicle-Detection/blob/master/examples/car_not_car.png)

I then explored different color spaces and different skimage.hog() parameters (orientations, pixels\_per\_cell, and cells\_per\_block). I grabbed random images from each of the two classes and displayed them to get a feel for what the skimage.hog() output looks like.

Here is an example using the YUV color space and HOG parameters of orientations=10, pixels\_per\_cell=(8, 8)and cells\_per\_block=(2, 2):



**2. Explain how you settled on your final choice of HOG parameters.**

In explore.ipynb, I started with an exhaustive search of hyperparameters and validation result optimization. I realized that some parameters can be tuned optimally with little correlation to other hyperparameters, so I prioritized these parameters to be trained and optimized first.

Beginning with some ballpark reasonable hyper parameter figures:

* Colorspace = RGB
* Orientations = 9
* Pixels per cell = 8
* Cells per block = 2

I optimized each layer *independently*, taking the optimal result from the previous stage as a basis for conducting the next search. Taking this approach ensured that training time did not blow up exponentially whilst allowed for a wide range of hyperparameter tuning.

This process yielded the optimal result with 0.9995 accuracy having:

* Colorspace = YUV
* Orientations = 12
* Pixels per cell = 8
* Cells per block = 2

Later on, through experimenting with processing the video, it was discovered that the quality of frames extracted differed vastly from the images used in the validation data from exploratory data analysis. Hence, colorspace was eventually settled to be ‘HLS’ instead, which performed better in generalizing for the video.

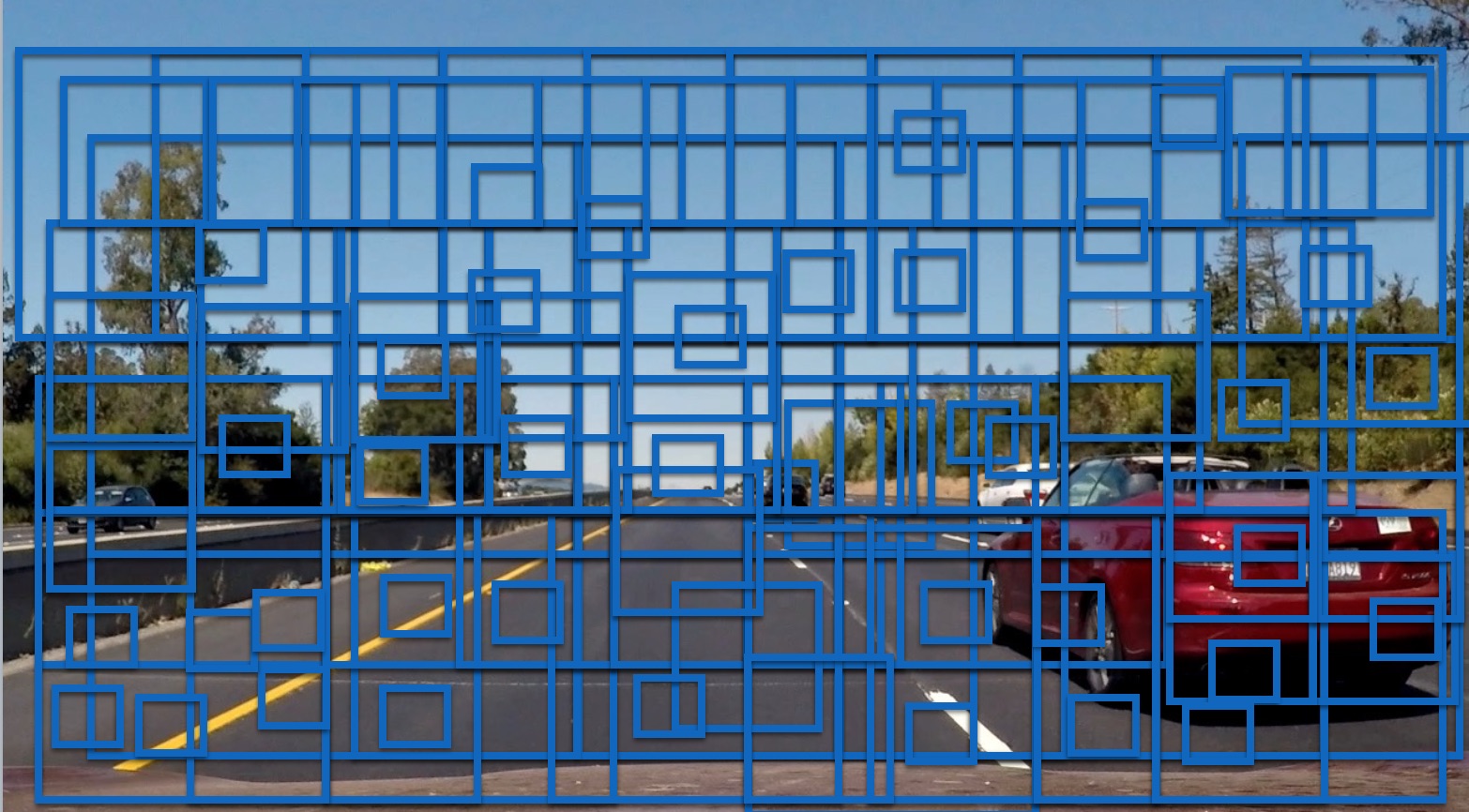
**3. Describe how (and identify where in your code) you trained a classifier using your selected HOG features (and color features if you used them).**

I trained a linear SVM using the HOG features for all the channels of the HLS images, concatenated with color-binned images resized to 16x16 pixels and color histograms binned into 32 segments for each color channel. See model.py#train\_model (around model.py:44-47) for more details.

**Sliding Window Search**

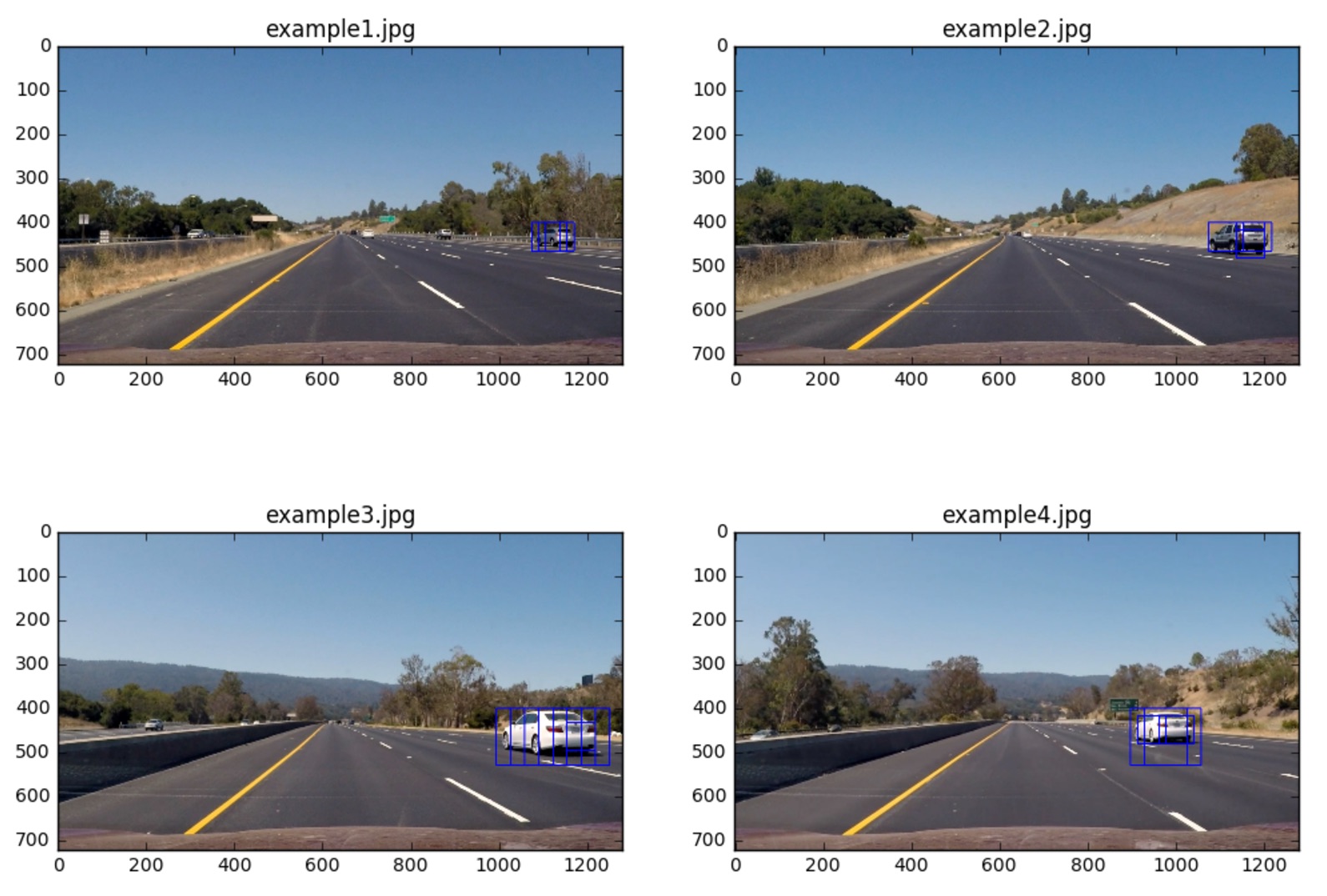
**1. Describe how (and identify where in your code) you implemented a sliding window search. How did you decide what scales to search and how much to overlap windows?**

I decided to search random window positions at random scales all over the image and came up with this (ok just kidding I didn't actually ;):

[](https://github.com/udacity/CarND-Vehicle-Detection/blob/master/examples/sliding_windows.jpg)

**2. Show some examples of test images to demonstrate how your pipeline is working. What did you do to optimize the performance of your classifier?**

Ultimately I searched on two scales using YCrCb 3-channel HOG features plus spatially binned color and histograms of color in the feature vector, which provided a nice result. Here are some example images:

**[](https://github.com/udacity/CarND-Vehicle-Detection/blob/master/examples/sliding_window.jpg)**

**Video Implementation**

**1. Provide a link to your final video output. Your pipeline should perform reasonably well on the entire project video (somewhat wobbly or unstable bounding boxes are ok as long as you are identifying the vehicles most of the time with minimal false positives.)**

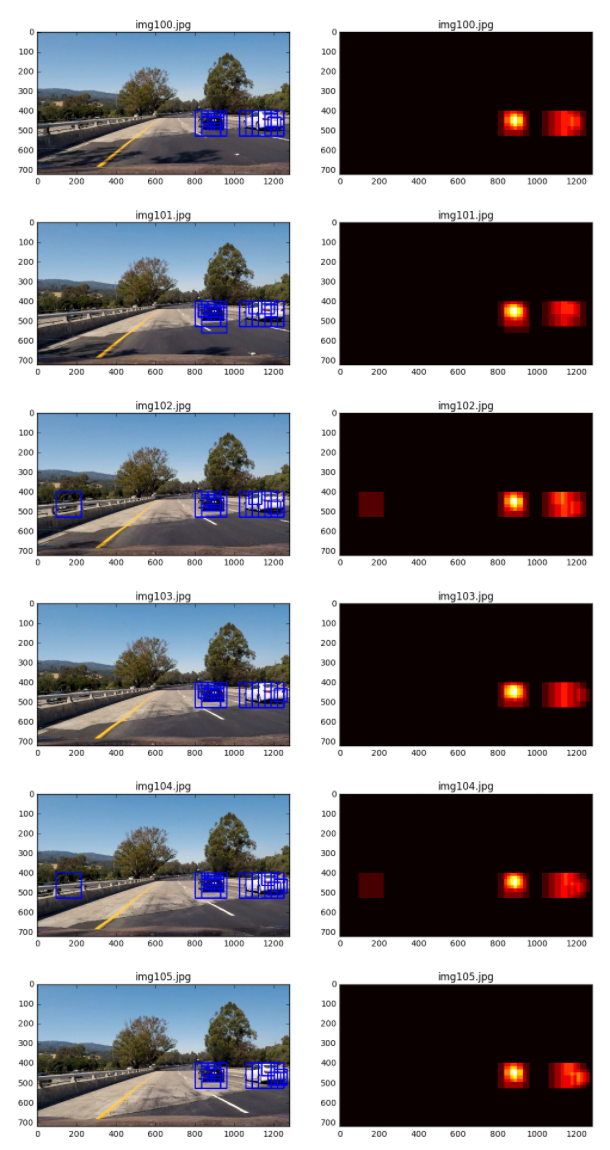
Here's a [link to my video result](https://github.com/udacity/CarND-Vehicle-Detection/blob/master/project_video.mp4)

**2. Describe how (and identify where in your code) you implemented some kind of filter for false positives and some method for combining overlapping bounding boxes.**

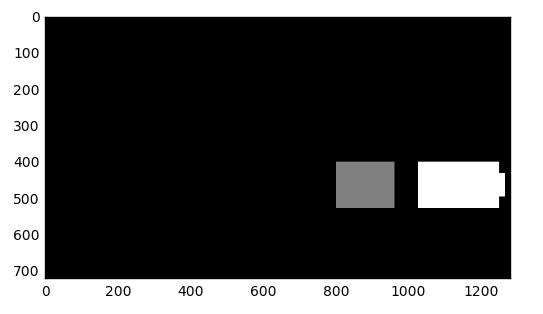
I recorded the positions of positive detections in each frame of the video. From the positive detections I created a heatmap and then thresholded that map to identify vehicle positions. I then used scipy.ndimage.measurements.label() to identify individual blobs in the heatmap. I then assumed each blob corresponded to a vehicle. I constructed bounding boxes to cover the area of each blob detected.

Here's an example result showing the heatmap from a series of frames of video, the result of scipy.ndimage.measurements.label() and the bounding boxes then overlaid on the last frame of video:

**Here are six frames and their corresponding heatmaps:**

[](https://github.com/udacity/CarND-Vehicle-Detection/blob/master/examples/bboxes_and_heat.png)

**Here is the output of scipy.ndimage.measurements.label() on the integrated heatmap from all six frames:**

[](https://github.com/udacity/CarND-Vehicle-Detection/blob/master/examples/labels_map.png)

**Here the resulting bounding boxes are drawn onto the last frame in the series:**

[](https://github.com/udacity/CarND-Vehicle-Detection/blob/master/examples/output_bboxes.png)

**Discussion**

**1. Briefly discuss any problems / issues you faced in your implementation of this project. Where will your pipeline likely fail? What could you do to make it more robust?**

Here I'll talk about the approach I took, what techniques I used, what worked and why, where the pipeline might fail and how I might improve it if I were going to pursue this project further.