Advanced Lane Finding Project

The goals / steps of this project are the following:

- Compute the camera calibration matrix and distortion coefficients given a set of chessboard images.
- Apply a distortion correction to raw images.
- Use color transforms, gradients, etc., to create a thresholded binary image.
- Apply a perspective transform to rectify binary image ("birds-eye view").
- Detect lane pixels and fit to find the lane boundary.
- Determine the curvature of the lane and vehicle position with respect to center.
- Warp the detected lane boundaries back onto the original image.
- Output visual display of the lane boundaries and numerical estimation of lane curvature and vehicle position.

Rubric 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 is a template writeup for this project you can use as a guide and a starting point.

You're reading it!

Camera Calibration

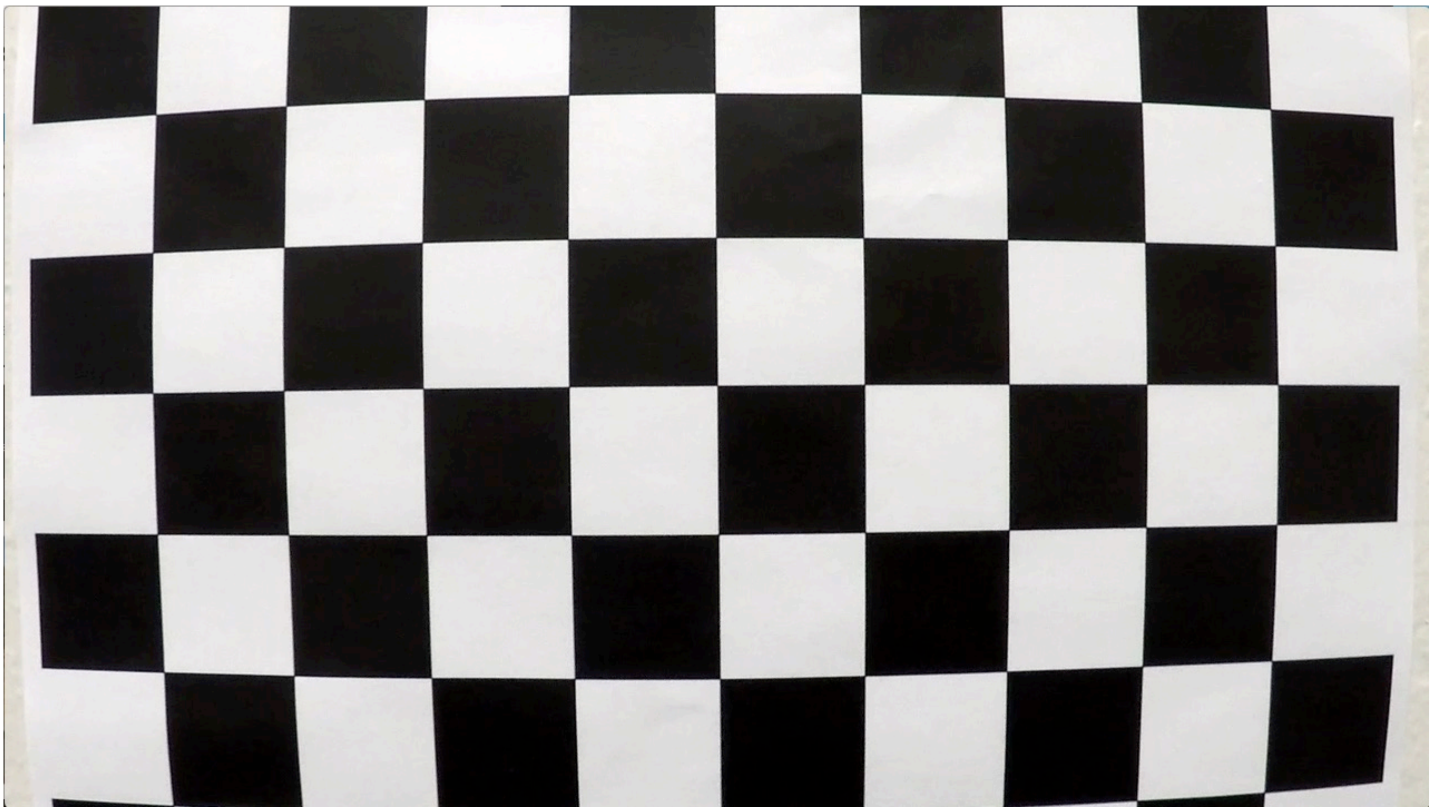
1. Briefly state how you computed the camera matrix and distortion coefficients. Provide an example of a distortion corrected calibration image.

The code for this step is contained in the first code cell of the IPython notebook located in "./src/calibrate.py".

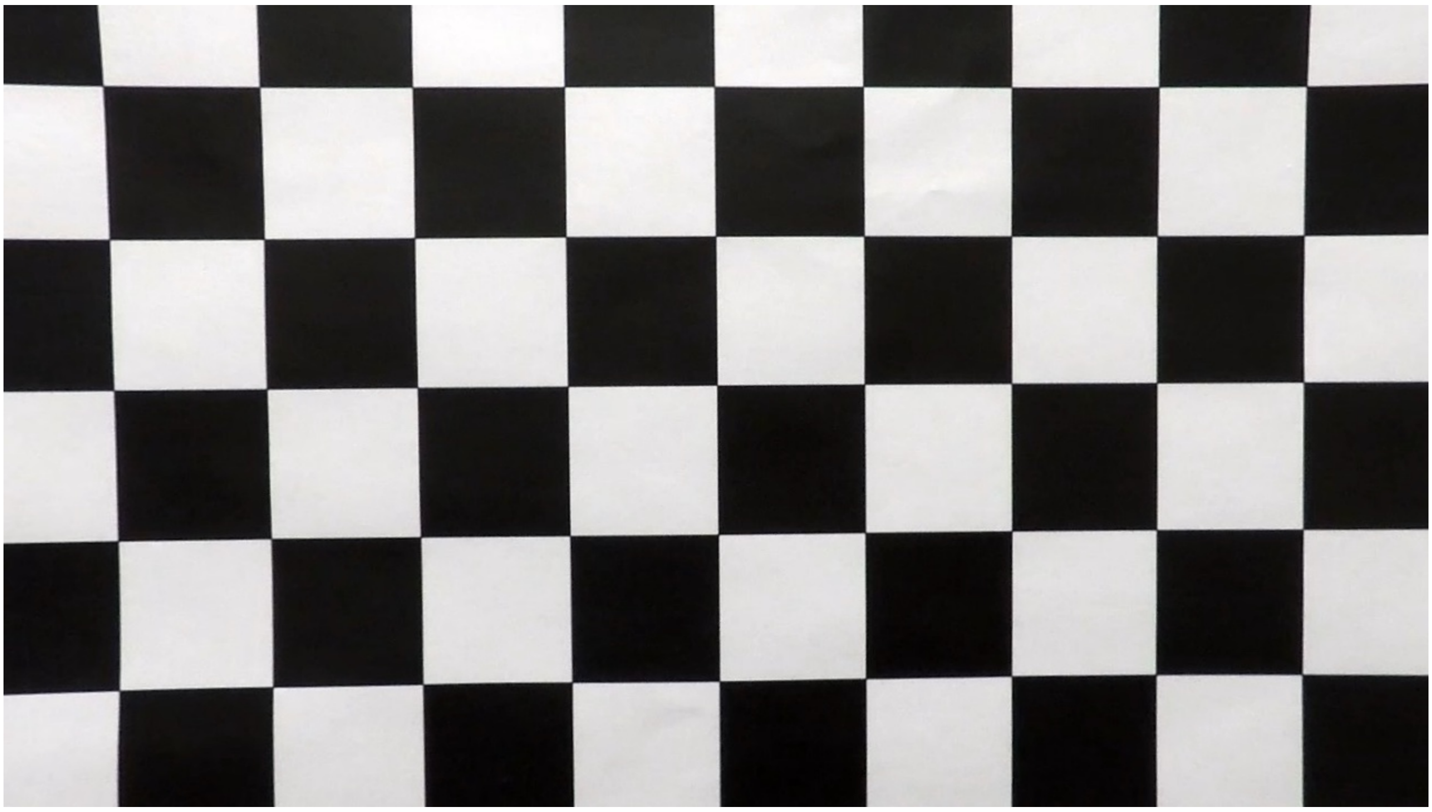
I start by preparing "object points", which will be the (x, y, z) coordinates of the chessboard corners in the world. Here I am assuming the chessboard is fixed on the (x, y) plane at z=0, such that the object points are the same for each calibration image. Thus, `objp` is just a replicated array of coordinates, and `objpoints` will be appended with a copy of it every time I successfully detect all chessboard corners in a test image. `imgpoints` will be appended with the (x, y) pixel position of each of the corners in the image plane with each successful chessboard detection.

I then used the output `objpoints` and `imgpoints` to compute the camera calibration and distortion coefficients using the `cv2.calibrateCamera()` function. I applied this distortion correction to the test image using the `cv2.undistort()` function and obtained this result:

Before

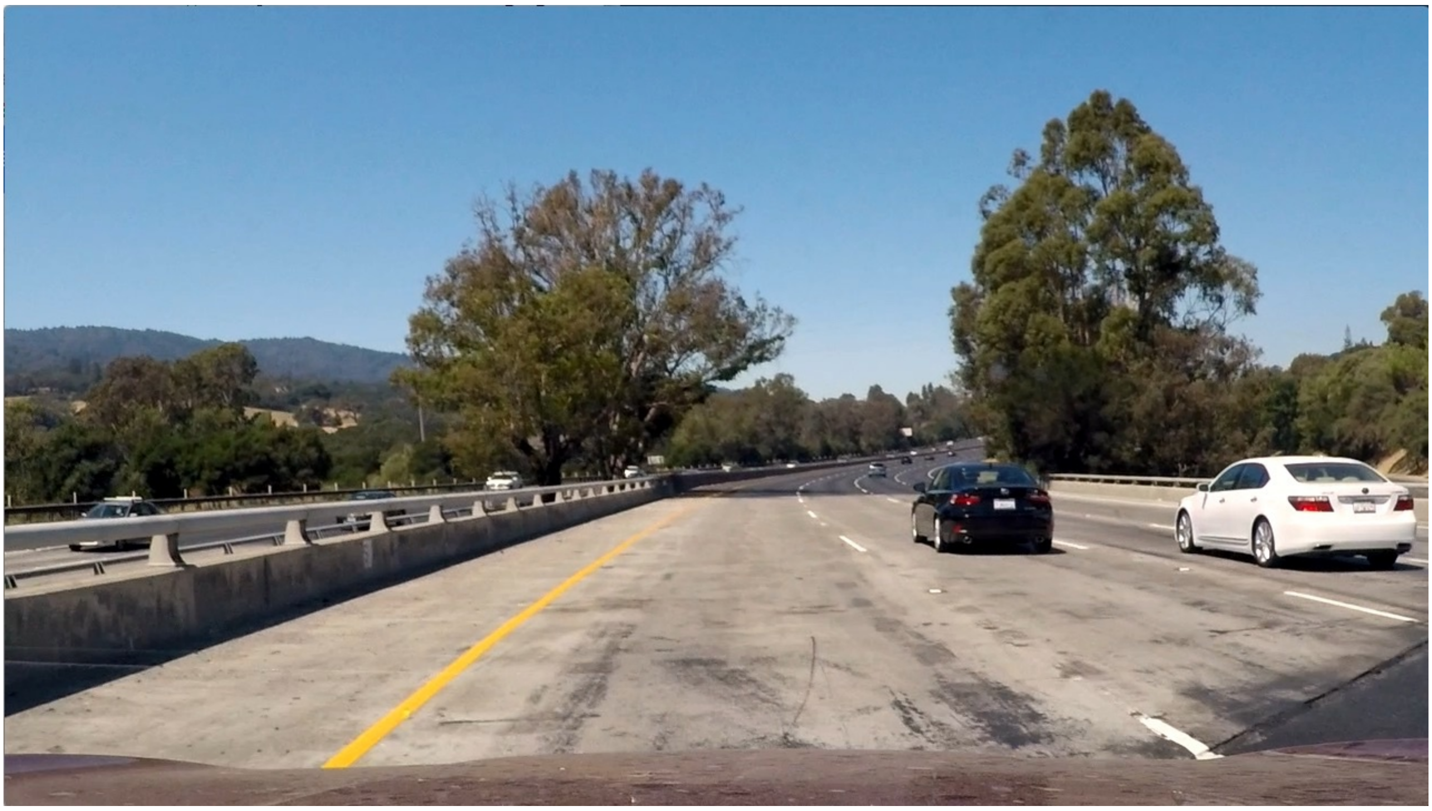


After



Pipeline (single images)

here we are processing on this test image:

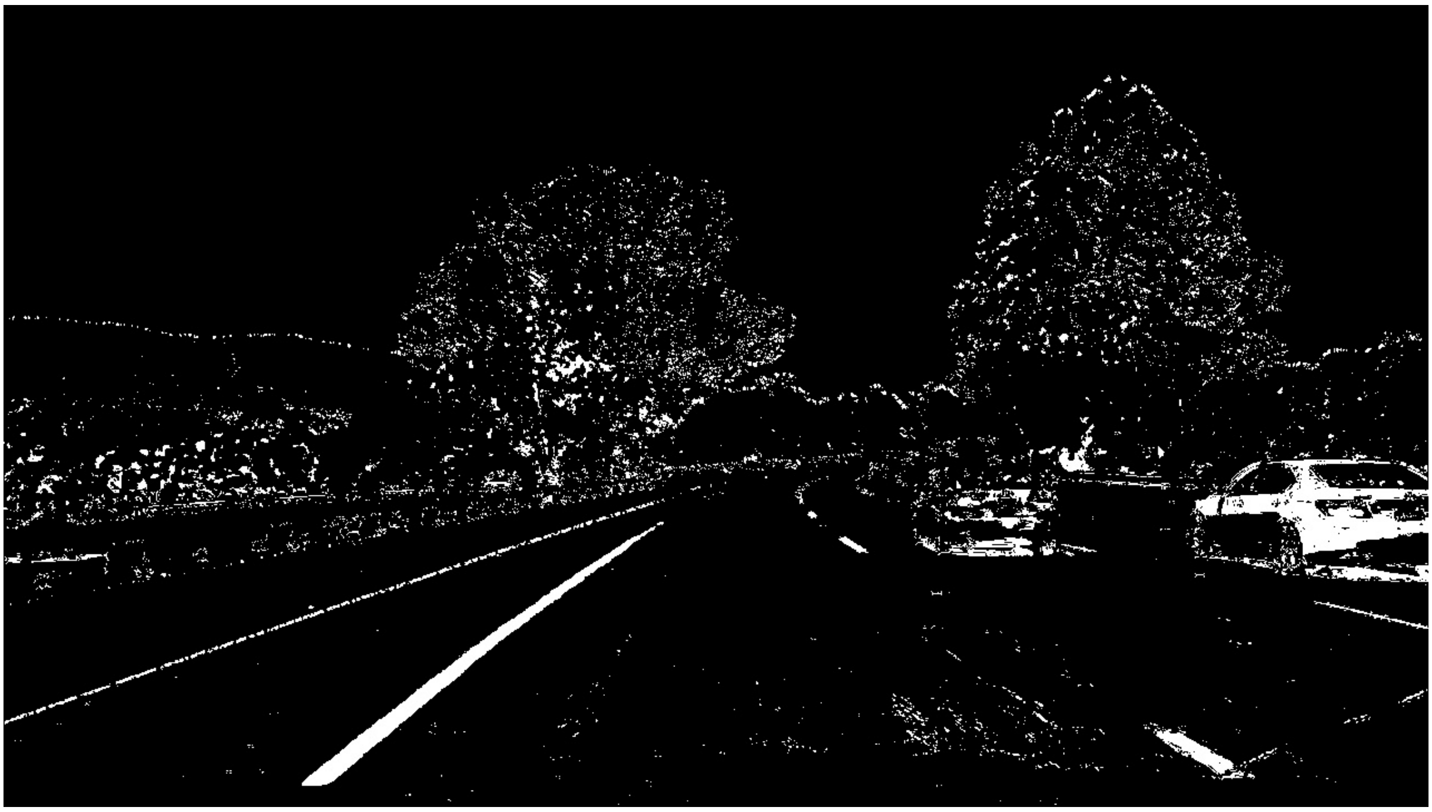


1. Provide an example of a distortion-corrected image.

To demonstrate this step, I will describe how I apply the distortion correction to one of the test images like this one:

2. Describe how (and identify where in your code) you used color transforms, gradients or other methods to create a thresholded binary image. Provide an example of a binary image result.

I used a combination of gradient x thresholds, gradient direction threshold and HLS S channel threshhold to generate a binary image (thresholding steps at lines 54 through 106 in `./src/line_detect.py`). The threshold of gradient x is from 20 to 100, the direction of gradient is between 0.7 to 1.3, and S channel value from 150 to 255. Here’s an example of my output for this step.



3. Describe how (and identify where in your code) you performed a perspective transform and provide an example of a transformed image.

The code for my perspective transform includes a function called `perspective_transform()` , which appears in lines 144 through 145 in the file `./src/line_detect.py` . The `perspective_transform()` function takes as inputs an image (`img`), as well as source (`src`) and destination (`dst`) points. I chose the hardcode the source and destination points in the following manner:

```
            src = np.array([
                [565, 470],
                [210, img_height],
                [1120, img_height],
                [715, 465]
            ], dtype=np.float32),
            dest = np.array([
                [210, 200],
                [210, img_height],
                [1120, img_height],
                [1120, 200]
            ], dtype=np.float32)
```

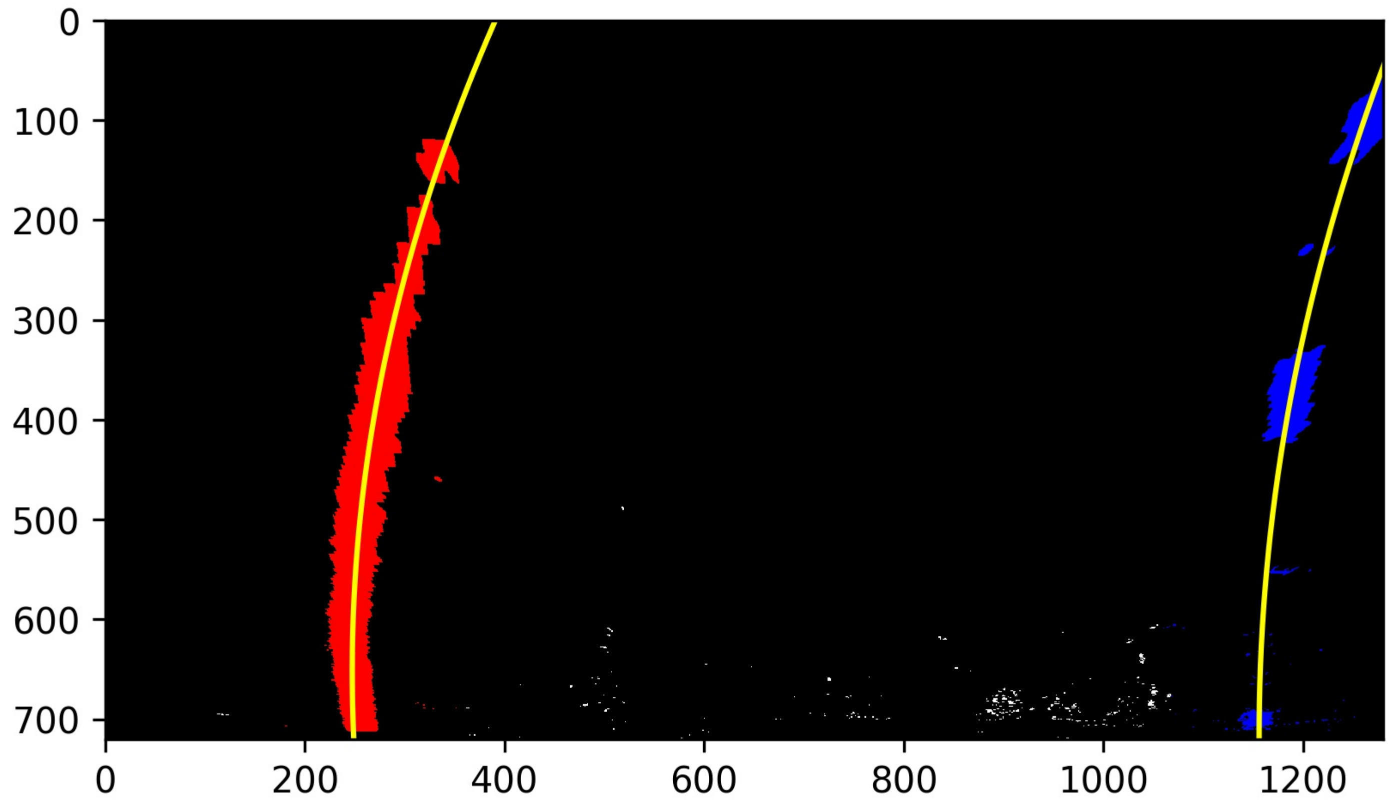
This resulted in the following source and destination points:

Source	Destination
565, 470	210, 200
210, 720	210, 720
1120, 720	1120, 720
715, 465	1120, 200

I verified that my perspective transform was working as expected by drawing the `src` and `dst` points onto a test image and its warped counterpart to verify that the lines appear parallel in the warped image.

4. Describe how (and identify where in your code) you identified lane-line pixels and fit their positions with a polynomial?

The code for my polynomial fitting includes two function called `extract_lanes_pixels()` and `poly_fit()` , which appears in lines 150 through 247 in the file `./src/line_detect.py` . `extract_lanes_pixels()` extracting the point in left and right lane with slide window histogram method, then `poly_fit()` take these point and fit my lane lines with a 2nd order polynomial kinda like this:



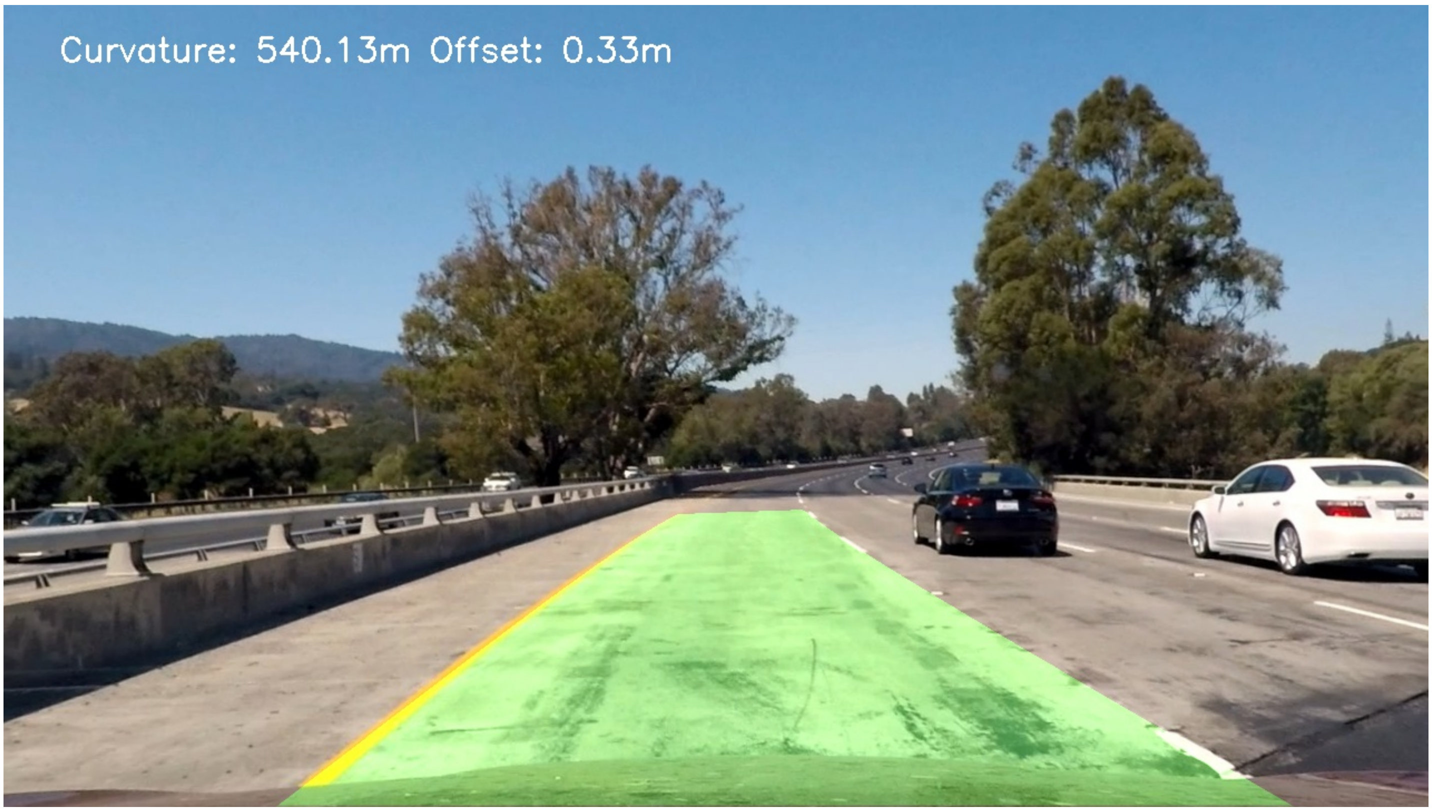
5. Describe how (and identify where in your code) you calculated the radius of curvature of the lane and the position of the vehicle with respect to center.

To calcaulate the radius, I did this in lines 252 through 256 in my code with `compute_curvature_and_root_point()` method, in `./src/line_detect.py`, by caculating the curvature radias next to the car which y locate at the botom of the image, and also I magnifyed the point `poly_fit()` generated to the scale in meter by times a ratio between meter and pixels.

And to calculate the offset, I assume the camera is located at the middle of the car. So I get the coordinate in meter of both lane line in the bottom which closest to the car, then calculate the absolute offset of the middle of this two point to the middle of the image. The code is located at `compute_offset()` method from line 258 to 261 in `src/line_detect.py`

6. Provide an example image of your result plotted back down onto the road such that the lane area is identified clearly.

I implemented this step in lines 256 through 275 in my code in `./src/line_detect.py` in the function `final_draw()`. Here is an example of my result on a test image:



Pipeline (video)

1. Provide a link to your final video output. Your pipeline should perform reasonably well on the entire project video (wobbly lines are ok but no catastrophic failures that would cause the car to drive off the road!).

Here's a link to my video result

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.

- the pipeline has assumed that the car is lay in middle of the lane and two lane lines on each side, but in the real world, this assumption is not nessicarily true.
- in the challenge video, it's failed at recognize the left lane, which get a dark shadow close to it, and it will enter the area of perspective transform, and disturb the line poly fit, so we can see the detected left line jump between the edge of shadow and the lane. At the end of challenge video, the shadow get far away from the lane line, now we can get the correct detection.

- Also in the challenge video, there are some patch lines paralles to the lane line and get quit close, will make it fail
- In the harder challenge video, the most serious reason to be failed is the turning is too sharp, and there are some bright area of the side of the rode introduced by the S channel, so the sliding window may miss tracking of the line, then make wrong prediction. Another problem is in my code, I take the bottom half of the perspective transformed image to make the histgram and to get the base of the two line, but in this video, too sharp turning will make the two line get overlapping in the histgram and bring error for the locate of base of line.