

# Project: Advanced Lane Finding

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## Project: Advanced Lane Finding



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## 1. Overview

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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.

## 2. Project Introduction

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As in the *Lane Lines P1* project, this project is also using the image processing technology to detect the lane on the road. The mainly used package is `cv2` provided by **OpenCV**. The process is firstly tested on the images and then finds the lanes on a movie.

## 3. Project Pipeline

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The workflow of the project is defined as below:

1. calculate the undistorted cheese board parameter and save in `calibration.p`
2. generate the perspective transform and region of interest of image based on undistorted test images
3. process the *Sobel Operator* on selected image
4. choose *HLS\_L + LAB\_B* as color space
5. get the lane lines by using sliding window and polynomial fit
6. calculate the curvature based on the polynomial fit
7. draw lines and draw data on test image
8. group the steps before and perform on videos

### 3.1 Undistorted Image

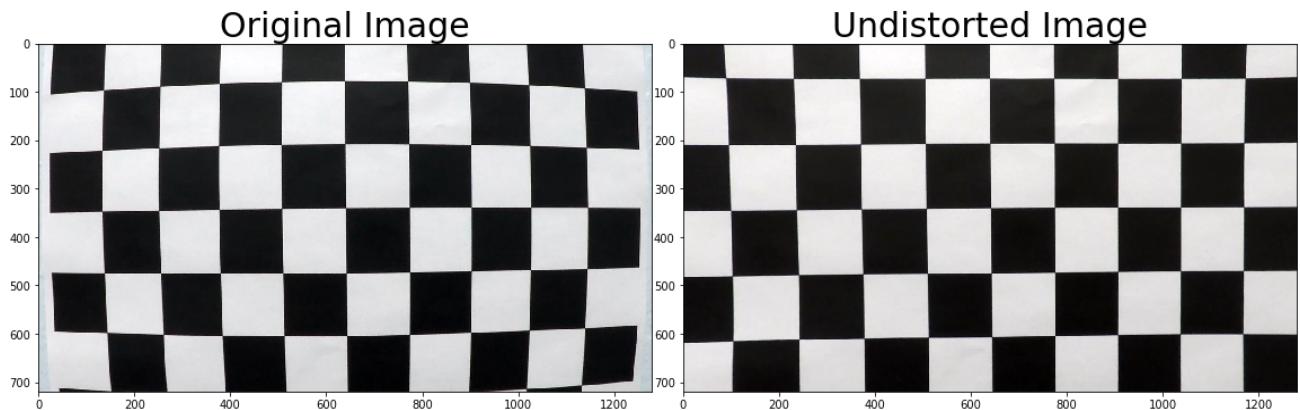
The code is directly taken over from the class.

```
1 import numpy as np
2 import cv2
3 import glob
4 import matplotlib.pyplot as plt
5 %matplotlib qt
6
7 # prepare object points, like (0,0,0), (1,0,0), (2,0,0) ....,(6,5,0)
8 objp = np.zeros((6*9,3), np.float32)
9 objp[:, :2] = np.mgrid[0:9,0:6].T.reshape(-1,2)
10
11 # Arrays to store object points and image points from all the images.
12 objpoints = [] # 3d points in real world space
13 imgpoints = [] # 2d points in image plane.
14
15 # Make a list of calibration images
16 images = glob.glob('./camera_cal/calibration*.jpg')
17
18 # Step through the list and search for chessboard corners
19 for fname in images:
20     img = cv2.imread(fname)
21     gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
22
23     # Find the chessboard corners
24     ret, corners = cv2.findChessboardCorners(gray, (9,6), None)
25
26     # If found, add object points, image points
27     if ret == True:
28         objpoints.append(objp)
29         imgpoints.append(corners)
30
31     # Draw and display the corners
32     img = cv2.drawChessboardCorners(img, (9,6), corners, ret)
33     cv2.imshow('img',img)
34     cv2.waitKey(500)
35
36 cv2.destroyAllWindows()
```

The parameters for undistortion is saved in `calibration.p` and the result is shown as below.

```
1 import pickle
2
3 # Test undistortion on an image
4 img = cv2.imread('./camera_cal/calibration1.jpg')
5 img_size = (img.shape[1], img.shape[0])
6
7 # Do camera calibration given object points and image points
8 ret, mtx, dist, rvecs, tvecs = cv2.calibrateCamera(objpoints, imgpoints, img_size, None, None)
9 dst = cv2.undistort(img, mtx, dist, None, mtx)
10
11 # Save the camera calibration result for later use (we won't worry about rvecs / tvecs)
12 dist_pickle = {}
13 dist_pickle["mtx"] = mtx
14 dist_pickle["dist"] = dist
15 pickle.dump( dist_pickle, open( "calibration.p", "wb" ) )
16 dst = cv2.cvtColor(dst, cv2.COLOR_BGR2RGB)
17 # Visualize undistortion
18 f, (ax1, ax2) = plt.subplots(1, 2, figsize=(20,10))
19 f.subplots_adjust(hspace = .2, wspace=.05)
20 ax1.imshow(img)
21 ax1.set_title('Original Image', fontsize=30)
22 ax2.imshow(dst)
23 ax2.set_title('Undistorted Image', fontsize=30)
```

*Undistorted cheese board:*



When the parameters and the function implement on the test images, the result of undistortion shows below.

```

1 # Undistort the image by using the saved parameters from cheeseboard
2 def cal_undistort(img):
3     # Use cv2.calibrateCamera and cv2.undistort()
4     with open('./calibration.p', mode='rb') as f:
5         dist_pickle = pickle.load(f)
6     mtx, dist = dist_pickle["mtx"], dist_pickle["dist"]
7     undist = cv2.undistort(img, mtx, dist, None, mtx)
8     h, w = undist.shape[:2]
9     return undist

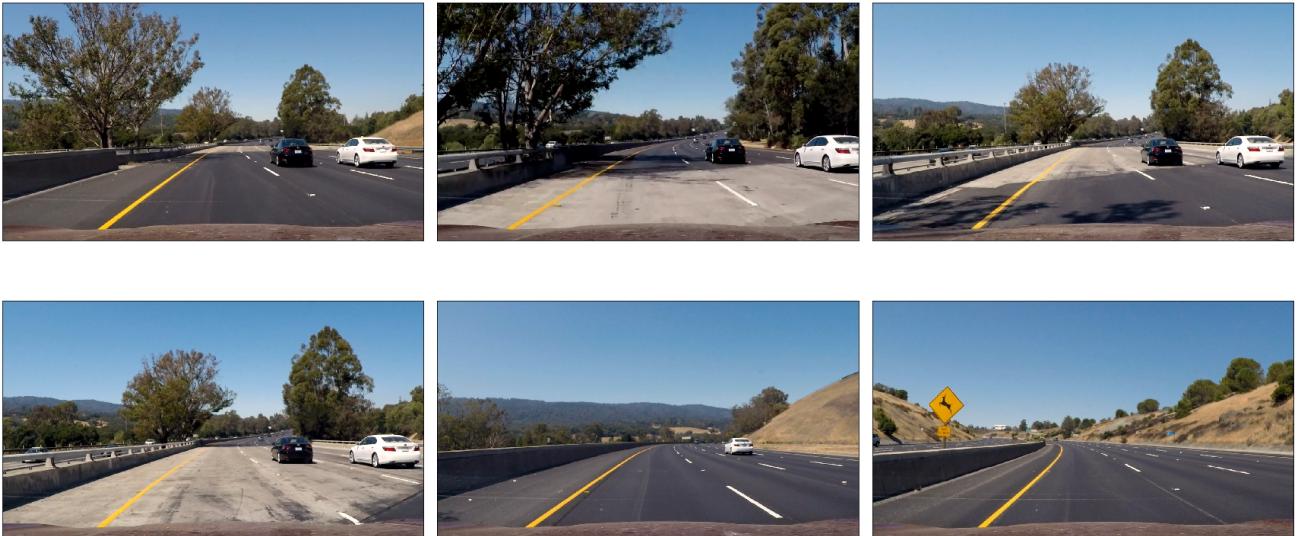
```

```

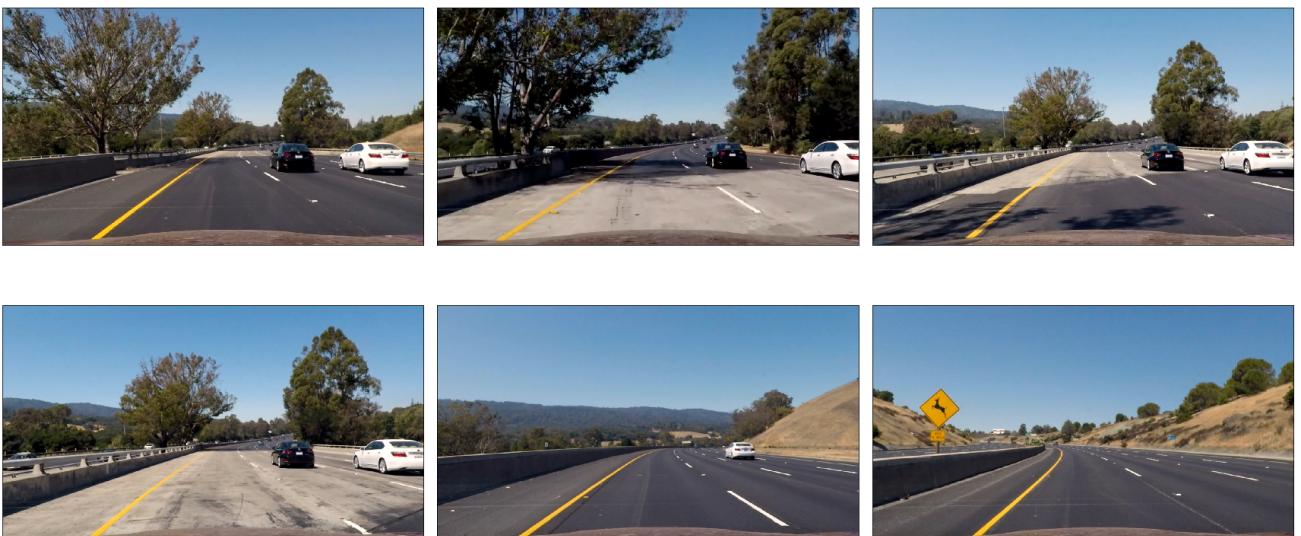
1 import matplotlib.image as mpimg
2 visualize("output_images/test_images.jpg",
3            (mpimg.imread(f) for f in (glob.glob("test_images/test*.jpg"))))
4 visualize("output_images/test_images_undistorted.jpg",
5           (cal_undistort(mpimg.imread(f)) for f in (glob.glob("test_images/test*.jpg"))))

```

*Original test images:*



*Undistorted test images:*



## 3.2 Perspective Transform

The *Perspective Transform* is able to transform the test image to bird-view image. In this part, the `region_of_interest` is also implemented, because the *Sobel Operator* can have a better detection on the lane lines.

```
1 # Perspective transform of image
2 def unwarp(img, src, dst):
3     h,w = img.shape[:2]
4     # use cv2.getPerspectiveTransform() to get M, the transform matrix, and Minv, the inverse
5     M = cv2.getPerspectiveTransform(src, dst)
6     Minv = cv2.getPerspectiveTransform(dst, src)
7     # use cv2.warpPerspective() to warp your image to a top-down view
8     warped = cv2.warpPerspective(img, M, (w,h), flags=cv2.INTER_LINEAR)
9     return warped, M, Minv
```

```
1 def region_of_interest(img, vertices):
2     #defining a blank mask to start with
3     mask = np.zeros_like(img)
4     #defining a 3 channel or 1 channel color to fill
5     #the mask with depending on the input image
6     if len(img.shape) > 2:
7         channel_count = img.shape[2] # i.e. 3 or 4 depending on your image
8         ignore_mask_color = (255,) * channel_count
9     else:
10        ignore_mask_color = 255
11
12    #filling pixels inside the polygon defined by "vertices" with the fill color
13    cv2.fillPoly(mask, vertices, ignore_mask_color)
14    #returning the image only where mask pixels are nonzero
15    masked_image = cv2.bitwise_and(img, mask)
16    return masked_image
```

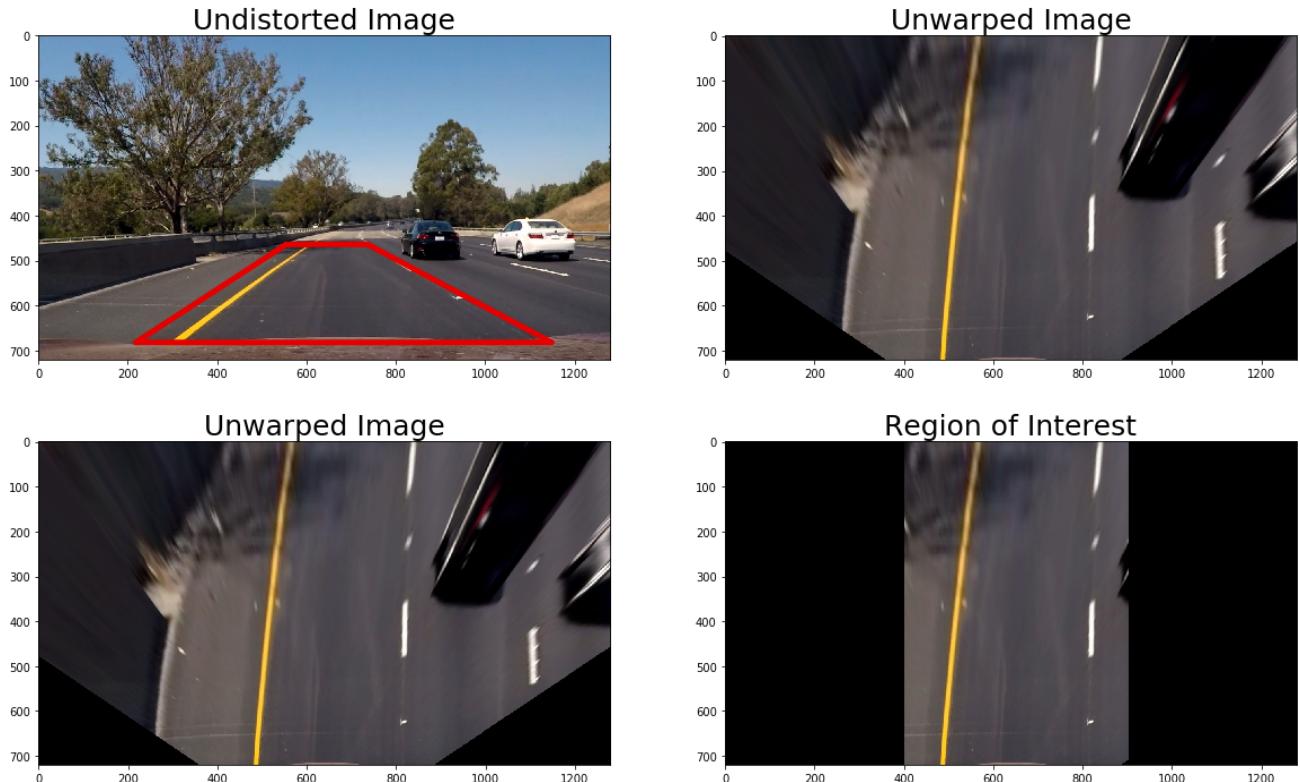
```
1 # Put together of perspective transform and extraction of region of interest
2 # define source and destination points for transform
3 src = np.float32([(555,464),
4                   (737,464),
5                   (218,682),
6                   (1149,682)])
7 dst = np.float32([(450,0),
8                   (w-450,0),
9                   (450,h),
10                  (w-450,h)])
11
12 for f in (glob.glob("test_images/test*.jpg")):
13     img = mpimg.imread(f)
14     undist_image = cal_undistort(img)
15     h,w = undist_image.shape[:2]
16     left_button = [400,h]
17     right_button = [900,h]
```

```

18     apex_left = [400,0]
19     apex_right = [900,0]
20     vertices = np.array([left_bottom, right_bottom, apex_right, apex_left], dtype =
21     np.int32)
22     unwrapped, M, Minv = unwarped(undist_image , src, dst)
23     img_select = region_of_interest(unwrapped, [vertices])
24     f, (ax1, ax2) = plt.subplots(1, 2, figsize=(20,10))
25     # Visualize unwarped
26     ax1.imshow(unwrapped)
27     ax1.set_title('Unwarped Image', fontsize=25)
28     ax2.imshow(img_select)
29     ax2.set_title('Region of Interest', fontsize=25)

```

One example of warped road image and region of interest:



### 3.3 Sobel Operator

Three *Sobel Operators* are implemented based on the class:

- `abs_sobel_thres(img, orient='x', thres=(20,100))`
- `mag_thres(img, sobel_kernel=9, mag_thres=(30,100))`
- `dir_thres(img, sobel_kernel=15, thres=(0.7,1.3))`

```

1 # Define a function that applies Sobel x or y,
2 # then takes an absolute value and applies a threshold.
3 def abs_sobel_thres(img, orient='x', thres=(20,100)):
4     # Apply the following steps to img
5     # 1) Convert to grayscale === or LAB L channel
6     gray = (cv2.cvtColor(img, cv2.COLOR_RGB2Lab))[:, :, 0]
7     # 2) Take the derivative in x or y given orient = 'x' or 'y'

```

```

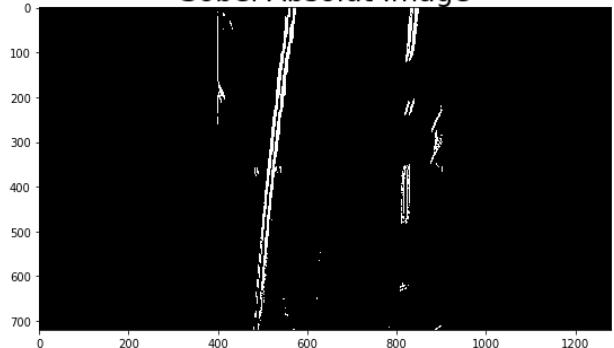
8     sobel = cv2.Sobel(gray, cv2.CV_64F, orient=='x', orient=='y')
9     # 3) Take the absolute value of the derivative or gradient
10    abs_sobel = np.absolute(sobel)
11    # 4) Scale to 8-bit (0 - 255) then convert to type = np.uint8
12    scaled_sobel = np.uint8(255*abs_sobel/np.max(abs_sobel))
13    # 5) Create a mask of 1's where the scaled gradient magnitude
14      # is > thresh_min and < thresh_max
15    sxbinary = np.zeros_like(scaled_sobel)
16    sxbinary[(scaled_sobel >= thres[0]) & (scaled_sobel <= thres[1])] = 1
17    # 6) Return this mask as your binary_output image
18    binary_output = sxbinary # Remove this line
19    return binary_output

```

Region of Interest



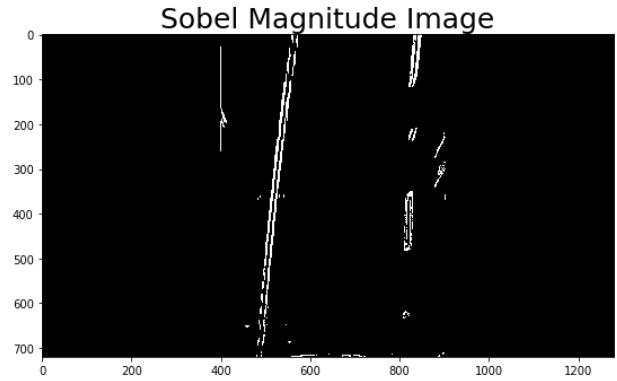
Sobel Absolut Image



```

1 def mag_thres(img, sobel_kernel=9, mag_thres=(30,100)):
2     # Apply the following steps to img
3     # 1) Convert to grayscale
4     gray = cv2.cvtColor(img, cv2.COLOR_RGB2GRAY)
5     # 2) Take the gradient in x and y separately
6     sobelx = cv2.Sobel(gray, cv2.CV_64F, 1, 0)
7     sobely = cv2.Sobel(gray, cv2.CV_64F, 0, 1)
8     # 3) Calculate the magnitude
9     mag_sobel = np.sqrt(np.square(sobelx) + np.square(sobely))
10    # 4) Scale to 8-bit (0 - 255) and convert to type = np.uint8
11    scaled_sobel = np.uint8(255*mag_sobel/np.max(mag_sobel))
12    # 5) Create a binary mask where mag thresholds are met
13    sxbinary = np.zeros_like(scaled_sobel)
14    sxbinary[(scaled_sobel >= mag_thres[0]) & (scaled_sobel <= mag_thres[1])] = 1
15    # 6) Return this mask as your binary_output image
16    binary_output = np.copy(sxbinary)
17    return binary_output

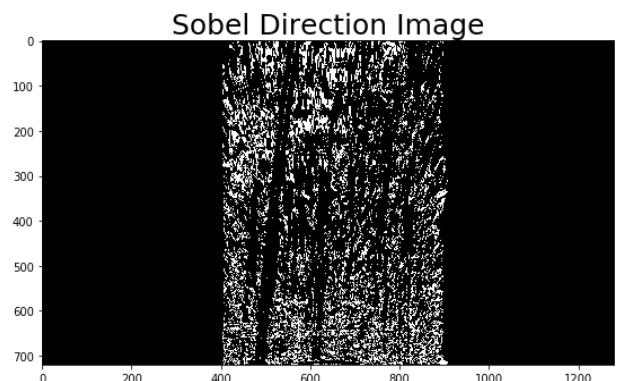
```



```

1 # Define a function that applies Sobel x and y,
2 # then computes the direction of the gradient
3 # and applies a threshold.
4 def dir_thres(img, sobel_kernel=15, thres=(0.7, 1.3)):
5     # Apply the following steps to img
6     # 1) Convert to grayscale
7     gray = cv2.cvtColor(img, cv2.COLOR_RGB2GRAY)
8     # 2) Take the gradient in x and y separately
9     sobelx = cv2.Sobel(gray, cv2.CV_64F, 1, 0, ksize=sobel_kernel)
10    sobely = cv2.Sobel(gray, cv2.CV_64F, 0, 1, ksize=sobel_kernel)
11    # 3) Take the absolute value of the x and y gradients
12    abs_sobelx = np.absolute(sobelx)
13    abs_sobely = np.absolute(sobely)
14    # 4) Use np.arctan2(abs_sobely, abs_sobelx) to calculate the direction of the gradient
15    grad_dir = np.arctan2(abs_sobely, abs_sobelx)
16    # 5) Create a binary mask where direction thresholds are met
17    binary_output = np.zeros_like(grad_dir)
18    binary_output[(grad_dir >= thres[0]) & (grad_dir <= thres[1])] = 1
19    # 6) Return this mask as your binary_output image
20    return binary_output

```



For *Sobel Operator*, last I tried to combine two sobel operators, mag + dir.

```

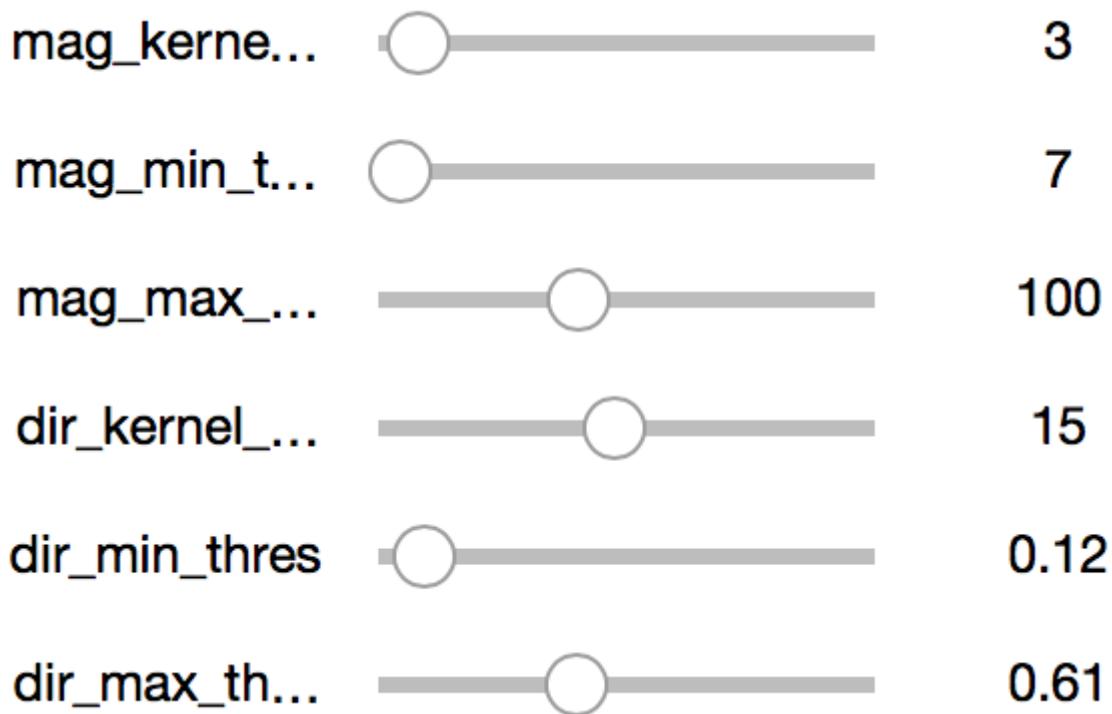
1 from __future__ import print_function
2 from ipywidgets import interact, interactive, fixed, interact_manual
3 import ipywidgets as widgets
4
5 def combined_thres(mag_kernel_size=3, mag_min_thres=7, mag_max_thres=100,
6                     dir_kernel_size=15, dir_min_thres=0.12, dir_max_thres=0.61):

```

```

6   for f in (glob.glob("test_images/test*.jpg")):
7       img = mpimg.imread(f)
8       img_select = Sobel_preprocess(img)
9       comb_magimg = mag_thres(img_select, mag_kernel_size, (mag_min_thres, mag_max_thres))
10      comb_dirimg = dir_thres(img_select, dir_kernel_size, (dir_min_thres, dir_max_thres))
11      combined = np.zeros_like(comb_magimg)
12      combined[((comb_magimg == 1) & (comb_dirimg == 1))] = 1
13      # Visualize sobel magnitude + direction threshold
14      f, (ax1, ax2) = plt.subplots(1, 2, figsize=(20,10))
15      f.subplots_adjust(hspace = .2, wspace=.05)
16      ax1.imshow(img)
17      ax1.set_title('Original Image', fontsize=30)
18      ax2.imshow(combined, cmap='gray')
19      ax2.set_title('Sobel Magnitude + Direction', fontsize=30)
20
21 interact(combined_thres, mag_kernel_size=(1,31,2),
22           mag_min_thres=(0,255),
23           mag_max_thres=(0,255),
24           dir_kernel_size=(1,31,2),
25           dir_min_thres=(0,np.pi/2,0.01),
26           dir_max_thres=(0,np.pi/2,0.01))
27
28

```





### 3.4 HLS\_L and LAB\_B

After the sobel combination, the result is not good enough to detect the lane lines. I try to use different color space and plot them. The method is to find a better way to detect lane lines.

The helper functions are mainly to transfer the RGB color space to specific color space like HLS\_S channel or LAB\_B channel.

```

1 # Define a function that thresholds the S-channel of HLS
2 # Use exclusive lower bound (>) and inclusive upper (=<)
3 def hls_sthres(img, thresh=(125, 255)):
4     # 1) Convert to HLS color space
5     hls = cv2.cvtColor(img, cv2.COLOR_RGB2HLS)
6     # 2) Apply a threshold to the S channel
7     binary_output = np.zeros_like(hls[:, :, 2])
8     binary_output[(hls[:, :, 2] > thresh[0]) & (hls[:, :, 2] <= thresh[1])] = 1
9     # 3) Return a binary image of threshold result
10    return binary_output
11
12
13 # Define a function that thresholds the L-channel of HLS
14 # Use exclusive lower bound (>) and inclusive upper (=<)
15 def hls_lthres(img, thresh=(220, 255)):
16     # 1) Convert to HLS color space
17     hls = cv2.cvtColor(img, cv2.COLOR_RGB2HLS)
18     hls_l = hls[:, :, 1]
19     hls_l = hls_l*(255/np.max(hls_l))
20     # 2) Apply a threshold to the L channel
21     binary_output = np.zeros_like(hls_l)
22     binary_output[(hls_l > thresh[0]) & (hls_l <= thresh[1])] = 1
23     # 3) Return a binary image of threshold result
24     return binary_output
25
26
27 # Define a function that thresholds the B-channel of LAB
28 # Use exclusive lower bound (>) and inclusive upper (=<), OR the results of the thresholds
# (B channel should capture
29 # yellows)
30 def lab_bthres(img, thresh=(190, 255)):
31     # 1) Convert to LAB color space

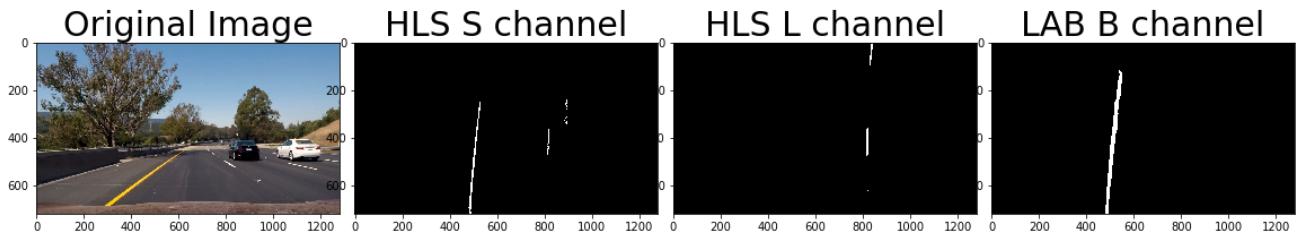
```

```

32     lab = cv2.cvtColor(img, cv2.COLOR_RGB2Lab)
33     lab_b = lab[:, :, 2]
34     # don't normalize if there are no yellows in the image
35     if np.max(lab_b) > 175:
36         lab_b = lab_b * (255 / np.max(lab_b))
37     # 2) Apply a threshold to the L channel
38     binary_output = np.zeros_like(lab_b)
39     binary_output[((lab_b > thresh[0]) & (lab_b <= thresh[1]))] = 1
40     # 3) Return a binary image of threshold result
41     return binary_output

```

The output image shows below.



It is easy to find out that HLS\_L channel is good at white lane line detection and LAB\_B is good at yellow lane lines detection. The `sobelpreprocess` is to combine those two color spaces, and the function is defined below.

```

1 def SobelProcess(unwrapped_img):
2     # HLS L-channel Threshold (using default parameters)
3     img_hls_L = hls_lthresh(unwrapped_img)
4
5     # Lab B-channel Threshold (using default parameters)
6     img_lab_B = lab_bthres(unwrapped_img)
7
8     # Combine HLS and Lab B channel thresholds
9     combined = np.zeros_like(img_lab_B)
10    combined[(img_hls_L == 1) | (img_lab_B == 1)] = 1
11    return combined

```

The whole sobel process pipeline is built.

```

1 def Sobel_preprocess(image):
2     undist_image = cal_undistort(image)
3     h, w = undist_image.shape[:2]
4     left_bottom = [400, h]
5     right_bottom = [900, h]
6     apex_left = [400, 0]
7     apex_right = [900, 0]
8     vertices = np.array([left_bottom, right_bottom, apex_right, apex_left], dtype =
np.int32)
9     src = np.float32([(555, 464),
10                      (737, 464),
11                      (218, 682),
12                      (1149, 682)])

```

```

13     dst = np.float32([(450,0),
14                         (w-450,0),
15                         (450,h),
16                         (w-450,h)])
17     unwrapped, M, Minv = un warp(undist_image , src, dst)
18     img_select = region_of_interest(unwrapped, [vertices])
19     return img_select
20
21 for f in (glob.glob("test_images/test*.jpg")):
22     img = mpimg.imread(f)
23     img_select = Sobel_preprocess(img)
24     comb_img = SobelProcess(img_select)
25     f, (ax1, ax2) = plt.subplots(1, 2, figsize=(20,10))
26     f.subplots_adjust(hspace = .2, wspace=.05)
27     ax1.imshow(img)
28     ax1.set_title('Original Image', fontsize=30)
29     ax2.imshow(comb_img, cmap='gray')
30     ax2.set_title('Sobel Processing Image', fontsize=30)

```

One of the output image shows below:



## 3.5 Sliding Window and Polynomial Fit

The `sliding_window` function is taken from the class directly and is defined as below.

```

1 def sliding_window(binary_warped):
2     # Assuming you have created a warped binary image called "binary_warped"
3     # Take a histogram of the bottom half of the image
4     histogram = np.sum(binary_warped[binary_warped.shape[0]//2:,:], axis=0)
5     # Create an output image to draw on and visualize the result
6     out_img = np.dstack((binary_warped, binary_warped, binary_warped))*255
7     # Find the peak of the left and right halves of the histogram
8     # These will be the starting point for the left and right lines
9     midpoint = np.int(histogram.shape[0]//2)
10    leftx_base = np.argmax(histogram[:midpoint])
11    rightx_base = np.argmax(histogram[midpoint:]) + midpoint
12
13    # Choose the number of sliding windows
14    nwindows = 10
15    # Set height of windows

```

```

16     window_height = np.int(binary_warped.shape[0]//nwindows)
17     # Identify the x and y positions of all nonzero pixels in the image
18     nonzero = binary_warped.nonzero()
19     nonzeroy = np.array(nonzero[0])
20     nonzerox = np.array(nonzero[1])
21     # Current positions to be updated for each window
22     leftx_current = leftx_base
23     rightx_current = rightx_base
24     # Set the width of the windows +/- margin
25     margin = 80
26     # Set minimum number of pixels found to recenter window
27     minpix = 40
28     # Create empty lists to receive left and right lane pixel indices
29     left_lane_inds = []
30     right_lane_inds = []
31     # Rectangle size
32     rectangle_data = []
33
34     # Step through the windows one by one
35     for window in range(nwindows):
36         # Identify window boundaries in x and y (and right and left)
37         win_y_low = binary_warped.shape[0] - (window+1)*window_height
38         win_y_high = binary_warped.shape[0] - window*window_height
39         win_xleft_low = leftx_current - margin
40         win_xleft_high = leftx_current + margin
41         win_xright_low = rightx_current - margin
42         win_xright_high = rightx_current + margin
43         rectangle_data.append((win_y_low, win_y_high, win_xleft_low, win_xleft_high,
44                                win_xright_low, win_xright_high))
45         # Identify the nonzero pixels in x and y within the window
46         good_left_inds = ((nonzeroy >= win_y_low) & (nonzeroy < win_y_high) &
47                           (nonzerox >= win_xleft_low) & (nonzerox < win_xleft_high)).nonzero()[0]
48         good_right_inds = ((nonzeroy >= win_y_low) & (nonzeroy < win_y_high) &
49                           (nonzerox >= win_xright_low) & (nonzerox < win_xright_high)).nonzero()[0]
50         # Append these indices to the lists
51         left_lane_inds.append(good_left_inds)
52         right_lane_inds.append(good_right_inds)
53         # If you found > minpix pixels, recenter next window on their mean position
54         if len(good_left_inds) > minpix:
55             leftx_current = np.int(np.mean(nonzerox[good_left_inds]))
56         if len(good_right_inds) > minpix:
57             rightx_current = np.int(np.mean(nonzerox[good_right_inds]))
58
59         # Concatenate the arrays of indices
60         left_lane_inds = np.concatenate(left_lane_inds)
61         right_lane_inds = np.concatenate(right_lane_inds)
62
63         # Extract left and right line pixel positions
64         leftx = nonzerox[left_lane_inds]
65         lefty = nonzeroy[left_lane_inds]
66         rightx = nonzerox[right_lane_inds]
67         righty = nonzeroy[right_lane_inds]
68

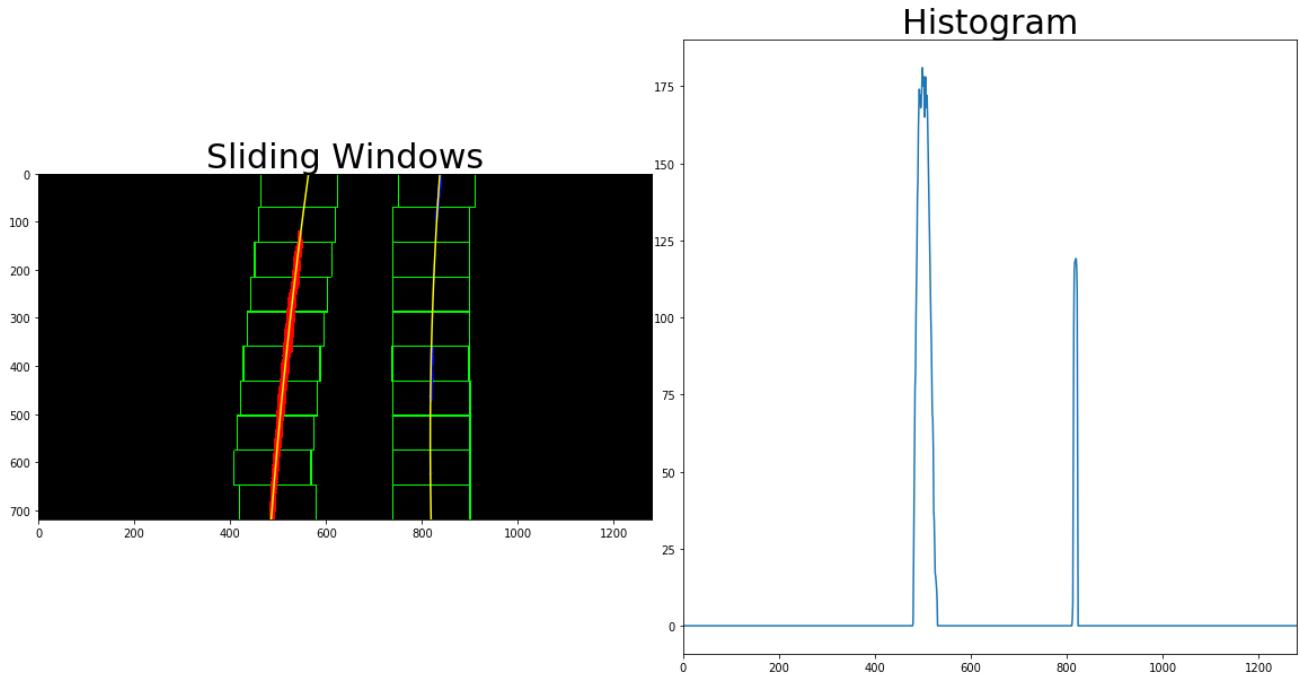
```

```

69     left_fit, right_fit = (None, None)
70     # Fit a second order polynomial to each
71     if len(leftx) != 0:
72         left_fit = np.polyfit(lefty, leftx, 2)
73     if len(rightx) != 0:
74         right_fit = np.polyfit(righty, rightx, 2)
75     return histogram, left_fit, right_fit, left_lane_inds, right_lane_inds, rectangle_data

```

The output on a single image with the histogram plot is:



The polynomial fit is to make the detected lane lines more smooth and easy to calculate the curvature on the following step.

Here I only define the second-degree polynomial function. The second-degree polynomial function can fit most of the case and the calculation cost is not high.

```

1 def polynomial_fit(binary_warped, left_fit, right_fit):
2     nonzero = binary_warped.nonzero()
3     nonzeroy = np.array(nonzero[0])
4     nonzerox = np.array(nonzero[1])
5     margin = 80
6     left_lane_inds = ((nonzerox > (left_fit[0]*(nonzeroy**2) + left_fit[1]*nonzeroy +
7                                     left_fit[2] - margin)) &
8                         (nonzerox < (left_fit[0]*(nonzeroy**2) + left_fit[1]*nonzeroy +
9                                     left_fit[2] + margin)))
10    right_lane_inds = ((nonzerox > (right_fit[0]*(nonzeroy**2) + right_fit[1]*nonzeroy +
11                               right_fit[2] - margin)) &
12                           (nonzerox < (right_fit[0]*(nonzeroy**2) + right_fit[1]*nonzeroy +
13                                         right_fit[2] + margin)))
14
15    # Again, extract left and right line pixel positions
16    leftx = nonzerox[left_lane_inds]
17    lefty = nonzero[0][left_lane_inds]

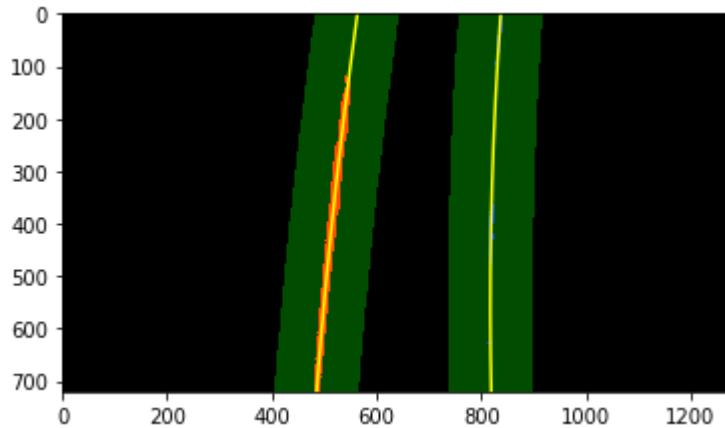
```

```

18     rightx = nonzerox[right_lane_inds]
19     righty = nonzeroy[right_lane_inds]
20
21     left_fit_new, right_fit_new = (None, None)
22     if len(leftx) != 0:
23         # Fit a second order polynomial to each
24         left_fit_new = np.polyfit(lefty, leftx, 2)
25     if len(rightx) != 0:
26         right_fit_new = np.polyfit(righty, rightx, 2)
27     return left_fit_new, right_fit_new, left_lane_inds, right_lane_inds

```

The output on single image is:



## 3.6 Curvature Calculation

The method to determine radius of curvature and distance from lane center based on binary image, polynomial fit, and L and R lane pixel indices.

```

1 def calc_curv_rad_and_center_dist(bin_img, l_fit, r_fit, l_lane_inds, r_lane_inds):
2     # Define conversions in x and y from pixels space to meters
3     # meters per pixel in y dimension, lane line is 3.048 meters
4     ym_per_pix = 3.048/100
5     # meters per pixel in x dimension, lane width is 3.7 meters
6     xm_per_pix = 3.7/378
7     left_curverad, right_curverad, center_dist = (0, 0, 0)
8     # Define y-value where we want radius of curvature
9     # the maximum y-value is considered for the bottom of the image
10    h = bin_img.shape[0]
11    ploty = np.linspace(0, h-1, h)
12    y_eval = np.max(ploty)
13
14    # Identify the x and y positions of all nonzero pixels in the image
15    nonzero = bin_img.nonzero()
16    nonzeroy = np.array(nonzero[0])
17    nonzerox = np.array(nonzero[1])
18    # Again, extract left and right line pixel positions
19    leftx = nonzerox[l_lane_inds]
20    lefty = nonzeroy[l_lane_inds]
21    rightx = nonzerox[r_lane_inds]

```

```

22     righty = nonzero[y[r_lane_inds]]
23
24     if len(leftx) != 0 and len(rightx) != 0:
25         # Fit new polynomials to x,y in world space
26         left_fit_cr = np.polyfit(lefty*ym_per_pix, leftx*xm_per_pix, 2)
27         right_fit_cr = np.polyfit(righty*ym_per_pix, rightx*xm_per_pix, 2)
28         # Calculate the new radii of curvature
29         left_curverad = ((1 + (2*left_fit_cr[0]*y_eval*ym_per_pix +
30                             left_fit_cr[1])**2)**1.5) / np.absolute(2*left_fit_cr[0])
31         right_curverad = ((1 + (2*right_fit_cr[0]*y_eval*ym_per_pix +
32                               right_fit_cr[1])**2)**1.5) / np.absolute(2*right_fit_cr[0])
33         # Now our radius of curvature is in meters
34
35     # Distance from center is image x midpoint - mean of l_fit and r_fit intercepts
36     if r_fit is not None and l_fit is not None:
37         car_position = bin_img.shape[1]/2
38         l_fit_x_int = l_fit[0]*h**2 + l_fit[1]*h + l_fit[2]
39         r_fit_x_int = r_fit[0]*h**2 + r_fit[1]*h + r_fit[2]
40         lane_center_position = (r_fit_x_int + l_fit_x_int) /2
41         center_dist = (car_position - lane_center_position) * xm_per_pix
42     return left_curverad, right_curverad, center_dist

```

The output message is:

```
Radius of curvature for example: 585.6218266179394 m, 1922.9803543221594 mDistance from lane
center for example: -0.22230240789210648 m
```

## 3.7 Single Image Pipeline

Before building the single image pipeline, there are two helper functions used to draw the lane lines and the curvature data on the image.

```

1 def draw_lane(original_img, binary_img, l_fit, r_fit, Minv):
2     new_img = np.copy(original_img)
3     if l_fit is None or r_fit is None:
4         return original_img
5     # Create an image to draw the lines on
6     warp_zero = np.zeros_like(binary_img).astype(np.uint8)
7     color_warp = np.dstack((warp_zero, warp_zero, warp_zero))
8
9     h,w = binary_img.shape
10    ploty = np.linspace(0, h-1, num=h)# to cover same y-range as image
11    left_fitx = l_fit[0]*ploty**2 + l_fit[1]*ploty + l_fit[2]
12    right_fitx = r_fit[0]*ploty**2 + r_fit[1]*ploty + r_fit[2]
13
14    # Recast the x and y points into usable format for cv2.fillPoly()
15    pts_left = np.array([np.transpose(np.vstack([left_fitx, ploty]))])
16    pts_right = np.array([np.flipud(np.transpose(np.vstack([right_fitx, ploty])))])
17    pts = np.hstack((pts_left, pts_right))
18
19    # Draw the lane onto the warped blank image

```

```

20     cv2.fillPoly(color_warp, np.int_(pts), (0,255, 0))
21     cv2.polylines(color_warp, np.int32([pts_left]), isClosed=False, color=(255,0,255),
22                     thickness=15)
23     cv2.polylines(color_warp, np.int32([pts_right]), isClosed=False, color=(0,255,255),
24                     thickness=15)
25
26     # Warp the blank back to original image space using inverse perspective matrix (Minv)
27     newwarp = cv2.warpPerspective(color_warp, Minv, (w, h))
28     # Combine the result with the original image
29     result = cv2.addWeighted(new_img, 1, newwarp, 0.5, 0)
30     return result
31
32
33 def draw_data(original_img, curv_rad, center_dist):
34     new_img = np.copy(original_img)
35     h = new_img.shape[0]
36     font = cv2.FONT_HERSHEY_DUPLEX
37     text = 'Curve radius: ' + '{:04.2f}'.format(curv_rad) + 'm'
38     cv2.putText(new_img, text, (40,70), font, 1.5, (200,255,155), 2, cv2.LINE_AA)
39     direction = ''
40     if center_dist > 0:
41         direction = 'right'
42     elif center_dist < 0:
43         direction = 'left'
44     abs_center_dist = abs(center_dist)
45     text = '{:04.3f}'.format(abs_center_dist) + 'm ' + direction + ' of center'
46     cv2.putText(new_img, text, (40,120), font, 1.5, (200,255,155), 2, cv2.LINE_AA)
47     return new_img

```

The pipeline for single image is to put the defined functions above together.

```

1 def process_image(img):
2     new_img = np.copy(img)
3     img_select = Sobel_preprocess(new_img)
4     binary_warped = SobelProcess(img_select)
5
6     # if both left and right lines were detected last frame, use polynomial_fit, otherwise
7     # use sliding_window
8     if not l_line.detected or not r_line.detected:
9         _, l_fit, r_fit, l_lane_inds, r_lane_inds, _ = sliding_window(binary_warped)
10    else:
11        l_fit, r_fit, l_lane_inds, r_lane_inds = polynomial_fit(binary_warped,
12                                         l_line.best_fit,
13                                         r_line.best_fit)
14
15    # invalidate both fits if the difference in their x-intercepts isn't around 350 px (+-
16    # 100 px)
17    if l_fit is not None and r_fit is not None:
18        # calculate x-intercept (bottom of image, x=image_height) for fits
19        h = img.shape[0]
20        l_fit_x_int = l_fit[0]*h**2 + l_fit[1]*h + l_fit[2]
21        r_fit_x_int = r_fit[0]*h**2 + r_fit[1]*h + r_fit[2]

```

```

22     x_int_diff = abs(r_fit_x_int-l_fit_x_int)
23     if abs(350 - x_int_diff) > 100:
24         l_fit = None
25         r_fit = None
26
27     l_line.add_fit(l_fit, l_lane_inds)
28     r_line.add_fit(r_fit, r_lane_inds)
29
30     # draw the current best fit if it exists
31     if l_line.best_fit is not None and r_line.best_fit is not None:
32         img_out1 = draw_lane(new_img, binary_warped, l_line.best_fit, r_line.best_fit,
Minv)
33         rad_l, rad_r, d_center = calc_curv_rad_and_center_dist(binary_warped,
34                                         l_line.best_fit,
35                                         r_line.best_fit,
36                                         l_lane_inds,
37                                         r_lane_inds)
38         img_out = draw_data(img_out1, (rad_l+rad_r)/2, d_center)
39     else:
40         img_out = new_img
41
42     diagnostic_output = False
43     if diagnostic_output:
44         # put together multi-view output
45         diag_img = np.zeros((720,1280,3), dtype=np.uint8)
46
47         # original output (top left)
48         diag_img[0:360,0:640,:] = cv2.resize(img_out,(640,360))
49
50         # binary overhead view (top right)
51         binary_warped = np.dstack((binary_warped*255, binary_warped*255,
52         binary_warped*255))
53         resized_img_bin = cv2.resize(binary_warped,(640,360))
54         diag_img[0:360,640:1280, :] = resized_img_bin
55
56         # overhead with all fits added (bottom right)
57         img_bin_fit = np.copy(binary_warped)
58         for i, fit in enumerate(l_line.current_fit):
59             img_bin_fit = plot_fit_onto_img(img_bin_fit, fit, (20*i+100,0,20*i+100))
60         for i, fit in enumerate(r_line.current_fit):
61             img_bin_fit = plot_fit_onto_img(img_bin_fit, fit, (0,20*i+100,20*i+100))
62             img_bin_fit = plot_fit_onto_img(img_bin_fit, l_line.best_fit, (255,255,0))
63             img_bin_fit = plot_fit_onto_img(img_bin_fit, r_line.best_fit, (255,255,0))
64             diag_img[360:720,640:1280,:] = cv2.resize(img_bin_fit,(640,360))
65
66         # diagnostic data (bottom left)
67         color_ok = (200,255,155)
68         color_bad = (255,155,155)
69         font = cv2.FONT_HERSHEY_DUPLEX
70         if l_fit is not None:
71             text = 'This fit L: ' + ' {:.6f}'.format(l_fit[0]) + \
72                   ' {:.6f}'.format(l_fit[1]) + \
73                   ' {:.6f}'.format(l_fit[2])

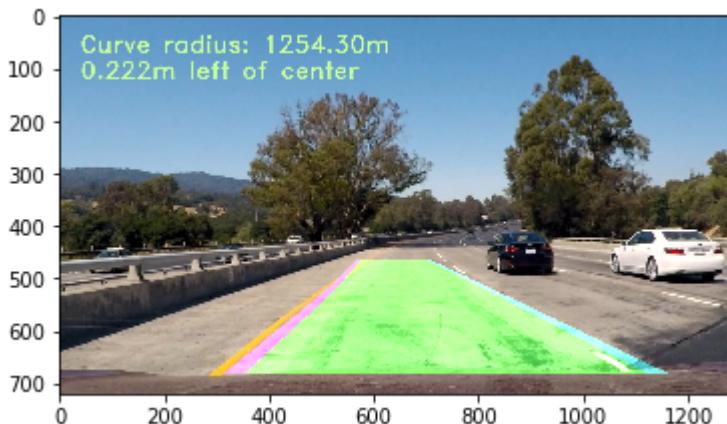
```

```

72     else:
73         text = 'This fit L: None'
74         cv2.putText(diag_img, text, (40,380), font, .5, color_ok, 1, cv2.LINE_AA)
75     if r_fit is not None:
76         text = 'This fit R: ' + ' {:.0f}'.format(r_fit[0]) + \
77                 ' {:.0f}'.format(r_fit[1]) + \
78                 ' {:.0f}'.format(r_fit[2])
79     else:
80         text = 'This fit R: None'
81         cv2.putText(diag_img, text, (40,400), font, .5, color_ok, 1, cv2.LINE_AA)
82     text = 'Best fit L: ' + ' {:.0f}'.format(l_line.best_fit[0]) + \
83             ' {:.0f}'.format(l_line.best_fit[1]) + \
84             ' {:.0f}'.format(l_line.best_fit[2])
85     cv2.putText(diag_img, text, (40,440), font, .5, color_ok, 1, cv2.LINE_AA)
86     text = 'Best fit R: ' + ' {:.0f}'.format(r_line.best_fit[0]) + \
87             ' {:.0f}'.format(r_line.best_fit[1]) + \
88             ' {:.0f}'.format(r_line.best_fit[2])
89     cv2.putText(diag_img, text, (40,460), font, .5, color_ok, 1, cv2.LINE_AA)
90     text = 'Diffs L: ' + ' {:.0f}'.format(l_line.diffs[0]) + \
91             ' {:.0f}'.format(l_line.diffs[1]) + \
92             ' {:.0f}'.format(l_line.diffs[2])
93     if l_line.diffs[0] > 0.001 or \
94         l_line.diffs[1] > 1.0 or \
95         l_line.diffs[2] > 100.:
96         diffs_color = color_bad
97     else:
98         diffs_color = color_ok
99     cv2.putText(diag_img, text, (40,500), font, .5, diffs_color, 1, cv2.LINE_AA)
100    text = 'Diffs R: ' + ' {:.0f}'.format(r_line.diffs[0]) + \
101            ' {:.0f}'.format(r_line.diffs[1]) + \
102            ' {:.0f}'.format(r_line.diffs[2])
103    if r_line.diffs[0] > 0.001 or \
104        r_line.diffs[1] > 1.0 or \
105        r_line.diffs[2] > 100.:
106        diffs_color = color_bad
107    else:
108        diffs_color = color_ok
109    cv2.putText(diag_img, text, (40,520), font, .5, diffs_color, 1, cv2.LINE_AA)
110    text = 'Good fit count L:' + str(len(l_line.current_fit))
111    cv2.putText(diag_img, text, (40,560), font, .5, color_ok, 1, cv2.LINE_AA)
112    text = 'Good fit count R:' + str(len(r_line.current_fit))
113    cv2.putText(diag_img, text, (40,580), font, .5, color_ok, 1, cv2.LINE_AA)
114
115    img_out = diag_img
116    return img_out

```

The single image shows below.



## 3.8 Video Process

As I did for P1, the video process is to call the `process_image` with the help of the package `from moviepy.editor import VideoFileClip`

Here is the code for the *project video* treatment.

```

1  from moviepy.editor import VideoFileClip
2
3  l_line = Line()
4  r_line = Line()
5  video_output1 = 'project_video_output.mp4'
6  video_input1 = VideoFileClip('project_video.mp4')
7  processed_video = video_input1.fl_image(process_image)
8  %time processed_video.write_videofile(video_output1, audio=False)
```

The output message shows the process of the video.

```

1  [MoviePy] >>> Building video project_video_output.mp4
2  [MoviePy] Writing video project_video_output.mp4
3  100%|██████████| 1260/1261 [02:37<00:00,  7.98it/s]
4  [MoviePy] Done.
5  [MoviePy] >>> Video ready: project_video_output.mp4
6
7  CPU times: user 2min 39s, sys: 20.8 s, total: 3min
8  Wall time: 2min 39s
```

The link to the *project video* is: [link to my video result](#)

---

## 4. Discussion

The pipeline works very well on the `project_video.mp4`, but it doesn't fit the lane lines in the `challenge_video.mp4` and almost doesn't work on the `harder_challenge_video.mp4`.

The main difference among those videos is, the project video has *clearer lane lines* and the color yellow and white has *higher saturation* and *higher contrast*. The intuitive difference is that the lane lines in the project video is easier to be recognized.

The amelioration would be, the image preprocessing could be used to adjust the image brightness, the contrast, the saturation and so on. This would let the Sobel Operator or the color space change more easier to detect the lane lines.