advanced_lane_finding

September 2, 2018

1 Advanced Lane Finding

```
In [1]: import cv2
        import matplotlib.pyplot as plt
        import matplotlib.image as mpimg
        import numpy as np
        import glob

        %matplotlib inline
```

```
In [2]: img = mpimg.imread('camera_cal/calibration11.jpg')
        image_shape = img.shape
        print(image_shape)
```

```
(720, 1280, 3)
```

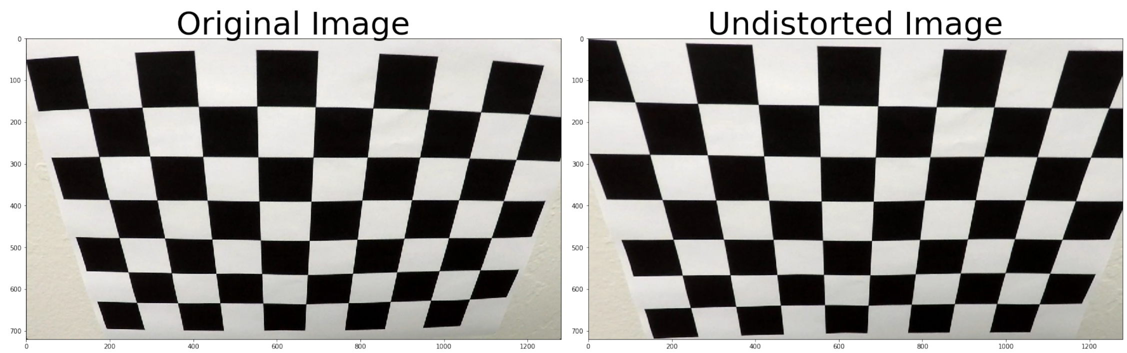
1.1 Step 1: Distortion Correction

In this step, I used the OpenCV functions cv2.findChessboardCorners to find corners in the chessboard each image and I used cv2.calibrateCamera to compute the camera matrix and distortion coefficients using corners of all images so I used cv2.undistort to undistort the images.

```
In [3]: nx = 9
        ny = 6

        objpoints = []
        imgpoints = []

        objp = np.zeros((nx*ny,3), np.float32)
        objp[:,:2] = np.mgrid[0:nx,0:ny].T.reshape(-1,2)

        fnames = glob.glob("camera_cal/calibration*.jpg")

        for fname in fnames:
            img = mpimg.imread(fname)
            gray = cv2.cvtColor(img, cv2.COLOR_RGB2GRAY)
```

```
        ret, corners = cv2.findChessboardCorners(gray, (nx,ny), None)
        if ret:
            objpoints.append(objp)
            imgpoints.append(corners)

    # use the object and image points to caliberate the camera and compute the camera matrix
    ret, cameraMatrix, distortionCoeffs, rvecs, tvecs = cv2.calibrateCamera(objpoints, imgpo
```

```
In [4]: img = mpimg.imread('camera_cal/calibration2.jpg')
        undistorted = cv2.undistort(img, cameraMatrix, distortionCoeffs, None, cameraMatrix)
        f, (ax1, ax2) = plt.subplots(1, 2, figsize=(24, 9))
        f.tight_layout()
        ax1.imshow(img)
        ax1.set_title('Original Image', fontsize=50)
        ax2.imshow(undistorted)
        ax2.set_title('Undistorted Image', fontsize=50)
        plt.subplots_adjust(left=0., right=1, top=0.9, bottom=0.)
```



1.2 Step 2: Create Thresholded Binary Image

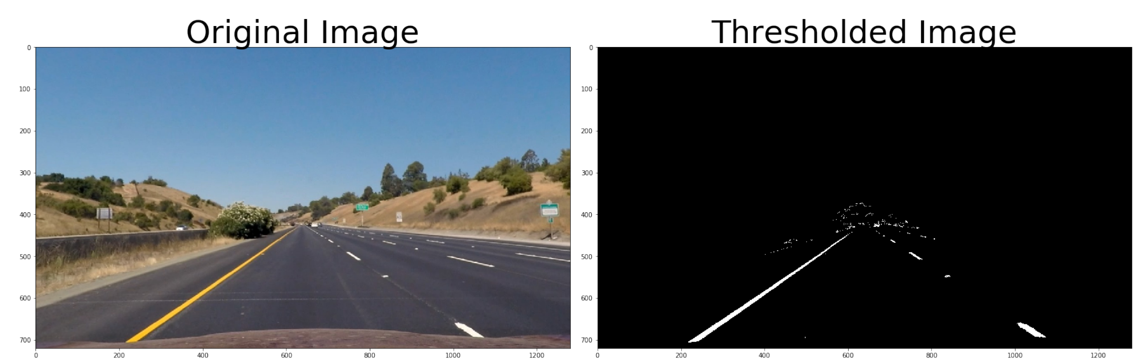
I used directional gradient in the axis X with thresholds of 30 and 90 degrees and R & G channel thresholds so that yellow lanes are detected well. L channel threshold so that we don't take into account edges generated due to shadows. S channel threshold since it does a good job of separating out white & yellow lanes.

```
In [5]: def thresholded_image(img):

            img = cv2.undistort(img, cameraMatrix, distortionCoeffs, None, cameraMatrix)

            # convert to gray scale
            gray = cv2.cvtColor(img, cv2.COLOR_RGB2GRAY)
            height, width = gray.shape

            # apply gradient threshold on the horizontal gradient
            sx_binary = abs_sobel_thresh(gray, 'x', 10, 200)
```

```
    # apply gradient direction threshold so that only edges closer to vertical are detec
    dir_binary = dir_threshold(gray, thresh=(np.pi/6, np.pi/2))

    # combine the gradient and direction thresholds.
    combined_condition = ((sx_binary == 1) & (dir_binary == 1))

    # R & G thresholds so that yellow lanes are detected well.
    color_threshold = 150
    R = img[:,:,0]
    G = img[:,:,1]
    color_combined = np.zeros_like(R)
    r_g_condition = (R > color_threshold) & (G > color_threshold)

    # color channel thresholds
    hls = cv2.cvtColor(img, cv2.COLOR_RGB2HLS)
    S = hls[:,:,2]
    L = hls[:,:,1]

    # S channel performs well for detecting bright yellow and white lanes
    s_thresh = (100, 255)
    s_condition = (S > s_thresh[0]) & (S <= s_thresh[1])

    # We put a threshold on the L channel to avoid pixels which have shadows and as a re
    l_thresh = (120, 255)
    l_condition = (L > l_thresh[0]) & (L <= l_thresh[1])

    # combine all the thresholds
    # A pixel should either be a yellowish or whiteish
    # And it should also have a gradient, as per our thresholds
    color_combined[(r_g_condition & l_condition) & (s_condition | combined_condition)] =

    # apply the region of interest mask
    mask = np.zeros_like(color_combined)
    region_of_interest_vertices = np.array([[0,height-1], [width/2, int(0.5*height)], [w
    cv2.fillPoly(mask, [region_of_interest_vertices], 1)
    thresholded = cv2.bitwise_and(color_combined, mask)

    return thresholded

def abs_sobel_thresh(gray, orient='x', thresh_min=0, thresh_max=255):
    if orient == 'x':
        sobel = cv2.Sobel(gray, cv2.CV_64F, 1, 0)
    else:
        sobel = cv2.Sobel(gray, cv2.CV_64F, 0, 1)
    abs_sobel = np.absolute(sobel)
    max_value = np.max(abs_sobel)
    binary_output = np.uint8(255*abs_sobel/max_value)
```

```
        threshold_mask = np.zeros_like(binary_output)
        threshold_mask[(binary_output >= thresh_min) & (binary_output <= thresh_max)] = 1
        return threshold_mask

    def dir_threshold(gray, sobel_kernel=3, thresh=(0, np.pi/2)):
        # Take the gradient in x and y separately
        sobel_x = cv2.Sobel(gray, cv2.CV_64F, 1, 0, ksize=sobel_kernel)
        sobel_y = cv2.Sobel(gray, cv2.CV_64F, 0, 1, ksize=sobel_kernel)
        # 3) Take the absolute value of the x and y gradients
        abs_sobel_x = np.absolute(sobel_x)
        abs_sobel_y = np.absolute(sobel_y)
        # 4) Use np.arctan2(abs_sobely, abs_sobelx) to calculate the direction of the gradie
        direction = np.arctan2(abs_sobel_y,abs_sobel_x)
        direction = np.absolute(direction)
        # 5) Create a binary mask where direction thresholds are met
        mask = np.zeros_like(direction)
        mask[(direction >= thresh[0]) & (direction <= thresh[1])] = 1
        # 6) Return this mask as your binary_output image
        return mask
```

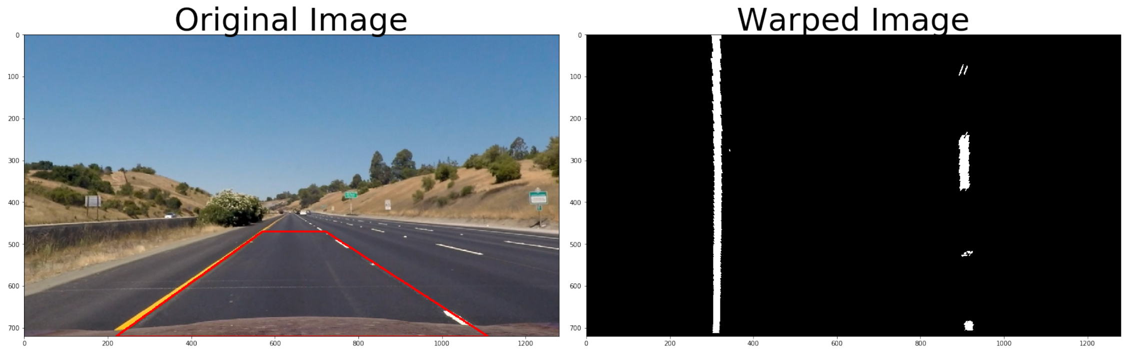
In [6]:
```
img = mpimg.imread('test_images/straight_lines1.jpg')
thresholded = thresholded_image(img)
img = cv2.undistort(img, cameraMatrix, distortionCoeffs, None, cameraMatrix)
cv2.imwrite('thresholded.jpg',thresholded)

# Plot the 2 images side by side
f, (ax1, ax2) = plt.subplots(1, 2, figsize=(24, 9))
f.tight_layout()
ax1.imshow(img)
ax1.set_title('Original Image', fontsize=50)
ax2.imshow(thresholded, cmap='gray')
ax2.set_title('Thresholded Image', fontsize=50)
plt.subplots_adjust(left=0., right=1, top=0.9, bottom=0.)
```



1.3 Step 3: Apply Perspective Transform

In this step I used the OpenCV functions cv2.getPerspectiveTransform and cv2.warpPerspective which take a matrix of four source points on the undistorted image and remaps them to four destination points on the warped image.

In [7]:
```
# Vertices extracted manually for performing a perspective transform
bottom_left = [220,720]
bottom_right = [1110, 720]
top_left = [570, 470]
top_right = [722, 470]

source = np.float32([bottom_left,bottom_right,top_right,top_left])

pts = np.array([bottom_left,bottom_right,top_right,top_left], np.int32)
pts = pts.reshape((-1,1,2))
copy = img.copy()
cv2.polylines(copy,[pts],True,(255,0,0), thickness=3)

# Destination points are chosen such that straight lanes appear more or less parallel in
bottom_left = [320,720]
bottom_right = [920, 720]
top_left = [320, 1]
top_right = [920, 1]

dst = np.float32([bottom_left,bottom_right,top_right,top_left])
M = cv2.getPerspectiveTransform(source, dst)
M_inv = cv2.getPerspectiveTransform(dst, source)
img_size = (image_shape[1], image_shape[0])

warped = cv2.warpPerspective(thresholded, M, img_size , flags=cv2.INTER_LINEAR)

f, (ax1, ax2) = plt.subplots(1, 2, figsize=(24, 9))
f.tight_layout()
ax1.imshow(copy)
ax1.set_title('Original Image', fontsize=50)
ax2.imshow(warped, cmap='gray')
ax2.set_title('Warped Image', fontsize=50)
plt.subplots_adjust(left=0., right=1, top=0.9, bottom=0.)
```



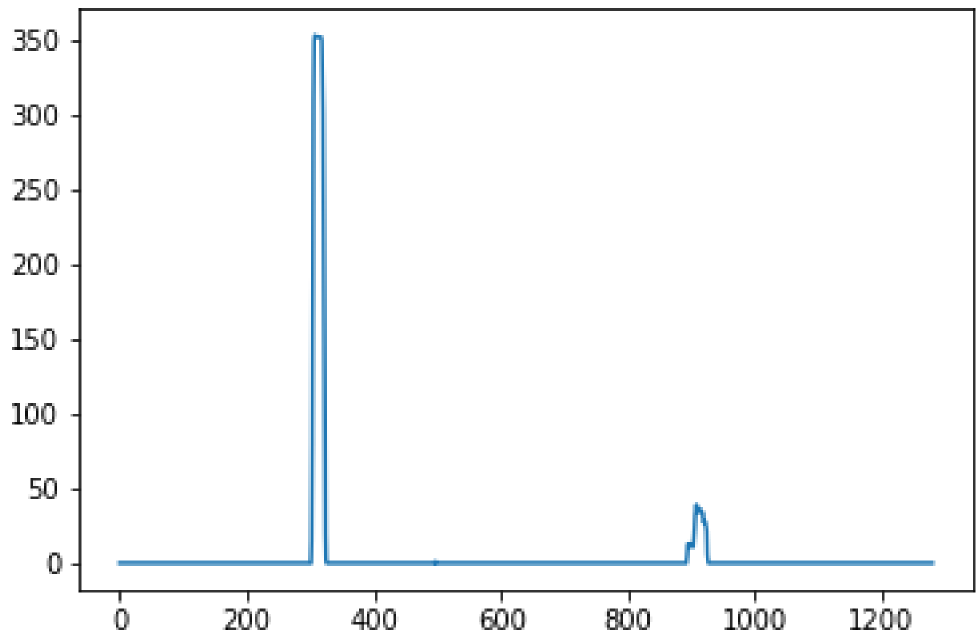
1.4 Step 4: Detect lane pixels and fit to find the lane boundary.

In this step I used peaks in a column histogram to find left and right lane pixels and then I perform a sliding window search, starting with the base likely positions of the 2 lanes, calculated from the histogram. I have used 10 windows of width 100 pixels. Since consecutive frames are likely to have lane lines in roughly similar positions, in this section we search around a margin of 50 pixels of the previously detected lane lines.

```
In [8]: histogram = np.sum(warped[warped.shape[0]//2:,:], axis=0)

        # Peak in the first half indicates the likely position of the left lane
        half_width = np.int(histogram.shape[0]/2)
        leftx_base = np.argmax(histogram[:half_width])

        # Peak in the second half indicates the likely position of the right lane
        rightx_base = np.argmax(histogram[half_width:]) + half_width

        print(leftx_base, rightx_base)
        plt.plot(histogram)
```

```
307 908
```

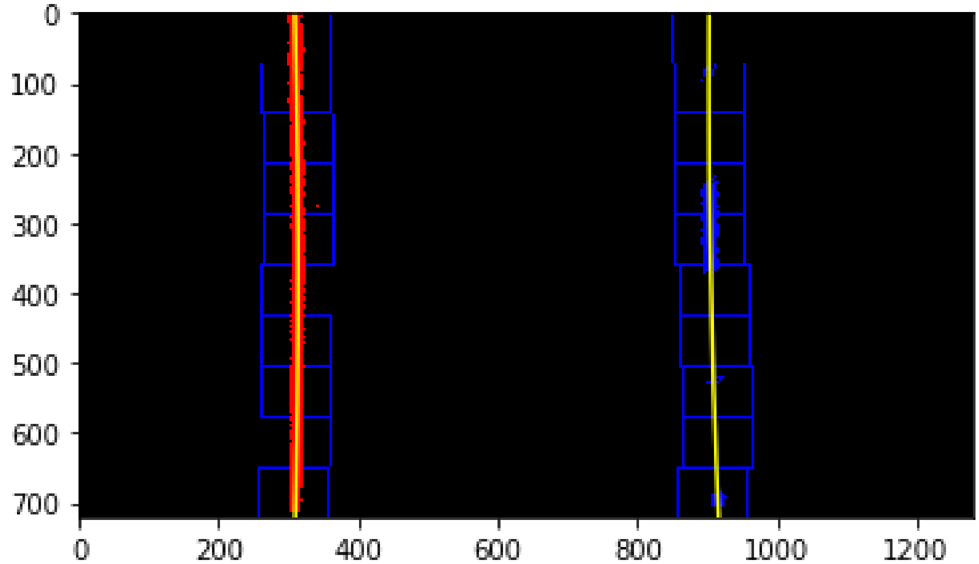
```
Out[8]: [<matplotlib.lines.Line2D at 0x7fbaeeb895f8>]
```




```
In [9]: out_img = np.dstack((warped, warped, warped))*255

        non_zeros = warped.nonzero()
        non_zeros_y = non_zeros[0]
        non_zeros_x = non_zeros[1]

        num_windows = 10
        num_rows = warped.shape[0]
        window_height = np.int(num_rows/num_windows)
        window_half_width = 50

        min_pixels = 100

        left_coordinates = []
        right_coordinates = []

        for window in range(num_windows):
            y_max = num_rows - window*window_height
            y_min = num_rows - (window+1)* window_height

            left_x_min = leftx_base - window_half_width
            left_x_max = leftx_base + window_half_width

            cv2.rectangle(out_img, (left_x_min, y_min), (left_x_max, y_max), [0,0,255],2)

            good_left_window_coordinates = ((non_zeros_x >= left_x_min) & (non_zeros_x <= left_x
```

```
            left_coordinates.append(good_left_window_coordinates)

            if len(good_left_window_coordinates) > min_pixels:
                leftx_base = np.int(np.mean(non_zeros_x[good_left_window_coordinates]))

            right_x_min = rightx_base - window_half_width
            right_x_max = rightx_base + window_half_width

            cv2.rectangle(out_img, (right_x_min, y_min), (right_x_max, y_max), [0,0,255],2)

            good_right_window_coordinates = ((non_zeros_x >= right_x_min) & (non_zeros_x <= righ
            right_coordinates.append(good_right_window_coordinates)

            if len(good_right_window_coordinates) > min_pixels:
                rightx_base = np.int(np.mean(non_zeros_x[good_right_window_coordinates]))

        left_coordinates = np.concatenate(left_coordinates)
        right_coordinates = np.concatenate(right_coordinates)

        out_img[non_zeros_y[left_coordinates], non_zeros_x[left_coordinates]] = [255,0,0]
        out_img[non_zeros_y[right_coordinates], non_zeros_x[right_coordinates]] = [0,0,255]

        left_x = non_zeros_x[left_coordinates]
        left_y = non_zeros_y[left_coordinates]

        polyfit_left = np.polyfit(left_y, left_x, 2)

        right_x = non_zeros_x[right_coordinates]
        right_y = non_zeros_y[right_coordinates]

        polyfit_right = np.polyfit(right_y, right_x, 2)

        y_points = np.linspace(0, num_rows-1, num_rows)

        left_x_predictions = polyfit_left[0]*y_points**2 + polyfit_left[1]*y_points + polyfit_le

        right_x_predictions = polyfit_right[0]*y_points**2 + polyfit_right[1]*y_points + polyfit

        plt.imshow(out_img)
        plt.plot(left_x_predictions, y_points, color='yellow')
        plt.plot(right_x_predictions, y_points, color='yellow')
        plt.xlim(0, warped.shape[1])
        plt.ylim(warped.shape[0],0)
```

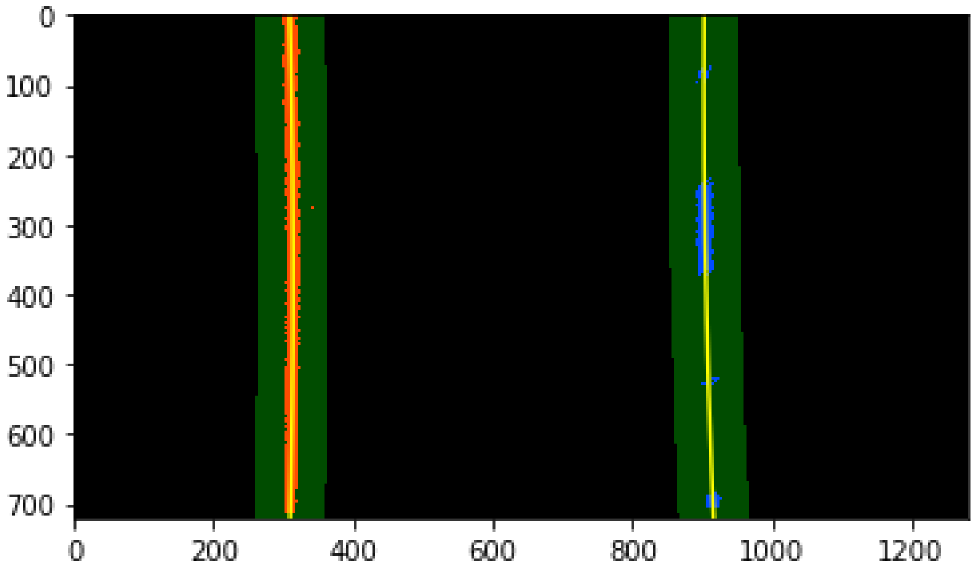
Out[9]: (720, 0)



In [10]:
```
margin = 50
out_img = np.dstack((warped, warped, warped))*255

left_x_predictions = polyfit_left[0]*non_zeros_y**2 + polyfit_left[1]*non_zeros_y + pol
left_coordinates = ((non_zeros_x >= left_x_predictions - margin) & (non_zeros_x <= left

right_x_predictions = polyfit_right[0]*non_zeros_y**2 + polyfit_right[1]*non_zeros_y +
right_coordinates = ((non_zeros_x >= right_x_predictions - margin) & (non_zeros_x <= ri

out_img[non_zeros_y[left_coordinates], non_zeros_x[left_coordinates]] = [255,0,0]
out_img[non_zeros_y[right_coordinates], non_zeros_x[right_coordinates]] = [0,0,255]


left_x = non_zeros_x[left_coordinates]
left_y = non_zeros_y[left_coordinates]

polyfit_left = np.polyfit(left_y, left_x, 2)

right_x = non_zeros_x[right_coordinates]
right_y = non_zeros_y[right_coordinates]

polyfit_right = np.polyfit(right_y, right_x, 2)

y_points = np.linspace(0, num_rows-1, num_rows)

left_x_predictions = polyfit_left[0]*y_points**2 + polyfit_left[1]*y_points + polyfit_l

right_x_predictions = polyfit_right[0]*y_points**2 + polyfit_right[1]*y_points + polyfi
```

```
window_img = np.zeros_like(out_img)

left_line_window_1 = np.array(np.transpose(np.vstack([left_x_predictions - margin, y_po

left_line_window_2 = np.array(np.flipud(np.transpose(np.vstack([left_x_predictions + ma

left_line_points = np.vstack((left_line_window_1, left_line_window_2))

cv2.fillPoly(window_img, np.int_([left_line_points]), [0,255, 0])

right_line_window_1 = np.array(np.transpose(np.vstack([right_x_predictions - margin, y_

right_line_window_2 = np.array(np.flipud(np.transpose(np.vstack([right_x_predictions +

right_line_points = np.vstack((right_line_window_1, right_line_window_2))

cv2.fillPoly(window_img, np.int_([right_line_points]), [0,255, 0])

result = cv2.addWeighted(out_img, 1, window_img, 0.3, 0)

plt.imshow(result)
plt.plot(left_x_predictions, y_points, color='yellow')
plt.plot(right_x_predictions, y_points, color='yellow')
plt.xlim(0, warped.shape[1])
plt.ylim(warped.shape[0],0)
```

Out[10]: (720, 0)



1.5 Step 5: Determine the curvature of the lane and vehicle position with respect to center

The radius of curvature is computed according to the formula and method described in the classroom material. Since we perform the polynomial fit in pixels and whereas the curvature has to be calculated in real world meters, we have to use a pixel to meter transformation and recompute the fit again.

The mean of the lane pixels closest to the car gives us the center of the lane. The center of the image gives us the position of the car.

```
In [11]: def measure_radius_of_curvature(x_values):
             ym_per_pix = 30/720 # meters per pixel in y dimension
             xm_per_pix = 3.7/700 # meters per pixel in x dimension
             # If no pixels were found return None
             y_points = np.linspace(0, num_rows-1, num_rows)
             y_eval = np.max(y_points)

             # Fit new polynomials to x,y in world space
             fit_cr = np.polyfit(y_points*ym_per_pix, x_values*xm_per_pix, 2)
             curverad = ((1 + (2*fit_cr[0]*y_eval*ym_per_pix + fit_cr[1])**2)**1.5) / np.absolut
             return curverad

         left_curve_rad = measure_radius_of_curvature(left_x_predictions)
         right_curve_rad = measure_radius_of_curvature(right_x_predictions)
         average_curve_rad = (left_curve_rad + right_curve_rad)/2
         curvature_string = "Radius of curvature: %.2f m" % average_curve_rad
         print(curvature_string)

         # compute the offset from the center
         lane_center = (right_x_predictions[719] + left_x_predictions[719])/2
         xm_per_pix = 3.7/700 # meters per pixel in x dimension
         center_offset_pixels = abs(img_size[0]/2 - lane_center)
         center_offset_mtrs = xm_per_pix*center_offset_pixels
         offset_string = "Center offset: %.2f m" % center_offset_mtrs
         print(offset_string)
```

```
Radius of curvature: 4709.52 m
Center offset: 0.14 m
```

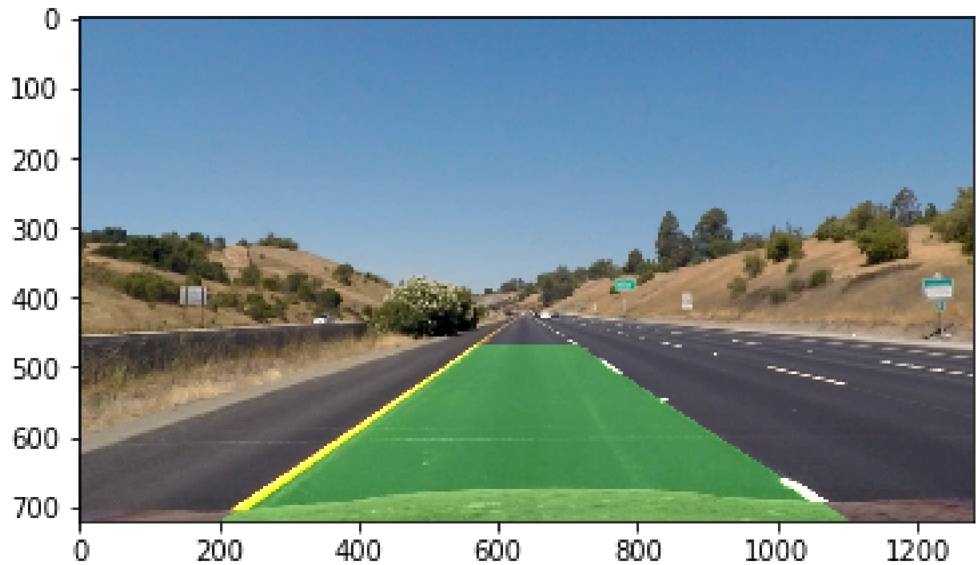
1.6 Step 6: Warp the detected lane boundaries back onto the original image.

In this step I apply the inverse transform in the detected lane in the original image.

```
In [12]: out_img = np.dstack((warped, warped, warped))*255

         y_points = np.linspace(0, num_rows-1, num_rows)
         left_line_window = np.array(np.transpose(np.vstack([left_x_predictions, y_points])))
         right_line_window = np.array(np.flipud(np.transpose(np.vstack([right_x_predictions, y_p
```

```
        line_points = np.vstack((left_line_window, right_line_window))
        cv2.fillPoly(out_img, np.int_([line_points]), [0,255, 0])
        unwarped = cv2.warpPerspective(out_img, M_inv, img_size , flags=cv2.INTER_LINEAR)
        result = cv2.addWeighted(img, 1, unwarped, 0.3, 0)
        plt.imshow(result)
```

Out[12]: <matplotlib.image.AxesImage at 0x7fbaeea525f8>



1.7 Final Pipeline

I combined all the code described to detect lanes in images and videos.

```
In [15]: # Some global variables
        polyfit_left=None
        polyfit_right=None

        past_good_left_lines = []
        past_good_right_lines = []

        running_mean_difference_between_lines = 0

        def get_line_predictions(non_zeros_x, non_zeros_y, left_coordinates, right_coordinates,
            """
                Given ncoordinates of non-zeros pixels and coordinates of non-zeros pixels with
                this function generates a prediction for the lane line.
            """
            left_x = non_zeros_x[left_coordinates]
            left_y = non_zeros_y[left_coordinates]
```

```
    # If no pixels were found return None
    if(left_y.size == 0 or left_x.size == 0):
        return None, None

    # Fit the polynomial
    polyfit_left = np.polyfit(left_y, left_x, 2)

    right_x = non_zeros_x[right_coordinates]
    right_y = non_zeros_y[right_coordinates]

    # If no pixels were found return None
    if(right_y.size == 0 or right_x.size == 0):
        return None, None

    # Fit the polynomial
    polyfit_right = np.polyfit(right_y, right_x, 2)

    # If no pixels were found return None
    y_points = np.linspace(0, num_rows-1, num_rows)

    # Generate the lane lines from the polynomial fit
    left_x_predictions = polyfit_left[0]*y_points**2 + polyfit_left[1]*y_points + polyf
    right_x_predictions = polyfit_right[0]*y_points**2 + polyfit_right[1]*y_points + po

    return left_x_predictions, right_x_predictions

def brute_search(warped):
    """
        This function searches for lane lines from scratch.
        Thresholding & performing a sliding window search.
    """
    non_zeros = warped.nonzero()
    non_zeros_y = non_zeros[0]
    non_zeros_x = non_zeros[1]

    num_rows = warped.shape[0]

    histogram = np.sum(warped[warped.shape[0]//2:,:], axis=0)

    half_width = np.int(histogram.shape[0]/2)
    leftx_base = np.argmax(histogram[:half_width])
    rightx_base = np.argmax(histogram[half_width:]) + half_width

    num_windows = 10
    window_height = np.int(num_rows/num_windows)
    window_half_width = 50
```

```
    min_pixels = 100

    left_coordinates = []
    right_coordinates = []

    for window in range(num_windows):
        y_max = num_rows - window*window_height
        y_min = num_rows - (window+1)* window_height

        left_x_min = leftx_base - window_half_width
        left_x_max = leftx_base + window_half_width

        good_left_window_coordinates = ((non_zeros_x >= left_x_min) & (non_zeros_x <= l
        left_coordinates.append(good_left_window_coordinates)

        if len(good_left_window_coordinates) > min_pixels:
            leftx_base = np.int(np.mean(non_zeros_x[good_left_window_coordinates]))

        right_x_min = rightx_base - window_half_width
        right_x_max = rightx_base + window_half_width

        good_right_window_coordinates = ((non_zeros_x >= right_x_min) & (non_zeros_x <=
        right_coordinates.append(good_right_window_coordinates)

        if len(good_right_window_coordinates) > min_pixels:
            rightx_base = np.int(np.mean(non_zeros_x[good_right_window_coordinates]))

    left_coordinates = np.concatenate(left_coordinates)
    right_coordinates = np.concatenate(right_coordinates)

    left_x_predictions, right_x_predictions = get_line_predictions(non_zeros_x, non_zer
    return left_x_predictions, right_x_predictions

def get_averaged_line(previous_lines, new_line):
    """
        This function computes an averaged lane line by averaging over previous good fr
    """

    # Number of frames to average over
    num_frames = 12

    if new_line is None:
        # No line was detected

        if len(previous_lines) == 0:
            # If there are no previous lines, return None
            return previous_lines, None
        else:
```

```
            # Else return the last line
            return previous_lines, previous_lines[-1]
    else:
        if len(previous_lines) < num_frames:
            # we need at least num_frames frames to average over
            previous_lines.append(new_line)
            return previous_lines, new_line
        else:
            # average over the last num_frames frames
            previous_lines[0:num_frames-1] = previous_lines[1:]
            previous_lines[num_frames-1] = new_line
            new_line = np.zeros_like(new_line)
            for i in range(num_frames):
                new_line += previous_lines[i]
            new_line /= num_frames
            return previous_lines, new_line


def get_mean_distance_between_lines(left_line, right_line, running_average):
    """
        Returns running weighted average of simple difference between left and right li
    """
    mean_distance = np.mean(right_line - left_line)
    if running_average == 0:
        running_average = mean_distance
    else:
        running_average = 0.9*running_average + 0.1*mean_distance
    return running_average


def pipeline_final(img):
    # global variables to store the polynomial coefficients of the line detected in the
    global polyfit_right
    global polyfit_left

    # global variables to store the line coordinates in previous n (=4) frames
    global past_good_right_lines
    global past_good_left_lines

    # global variable which contains running average of the mean difference between lef
    global running_mean_difference_between_lines

    img_shape = img.shape
    img_size = (image_shape[1], image_shape[0])

    # get thresholded image
    thresholded = thresholded_image(img)
```

```
# perform a perspective transform
warped = cv2.warpPerspective(thresholded, M, img_size , flags=cv2.INTER_LINEAR)

out_img = np.dstack((warped, warped, warped))*255

non_zeros = warped.nonzero()
non_zeros_y = non_zeros[0]
non_zeros_x = non_zeros[1]

num_rows = warped.shape[0]
y_points = np.linspace(0, num_rows-1, num_rows)

if (polyfit_left is None) or (polyfit_right is None):
    # If the polynomial coefficients of the previous frames are None then perform a
    brute = True
    left_x_predictions, right_x_predictions = brute_search(warped)
else:
    # Else search in a margin of 100 pixels on each side of the pervious polynomial
    brute = False
    margin = 100
    left_x_predictions = polyfit_left[0]*non_zeros_y**2 + polyfit_left[1]*non_zeros
    left_coordinates = ((non_zeros_x >= left_x_predictions - margin) & (non_zeros_x

    right_x_predictions = polyfit_right[0]*non_zeros_y**2 + polyfit_right[1]*non_ze
    right_coordinates = ((non_zeros_x >= right_x_predictions - margin) & (non_zeros

    left_x_predictions, right_x_predictions = get_line_predictions(non_zeros_x, non

if (left_x_predictions is None or right_x_predictions is None):
    if not brute:
        left_x_predictions, right_x_predictions = brute_search(warped)

bad_lines = False

if (left_x_predictions is None or right_x_predictions is None):
    bad_lines = True
else:
    mean_difference = np.mean(right_x_predictions - left_x_predictions)

    if running_mean_difference_between_lines == 0:
        running_mean_difference_between_lines = mean_difference

    if (mean_difference < 0.7*running_mean_difference_between_lines or mean_differe
        bad_lines = True
        if not brute:
            left_x_predictions, right_x_predictions = brute_search(warped)
            if (left_x_predictions is None or right_x_predictions is None):
                bad_lines = True
```

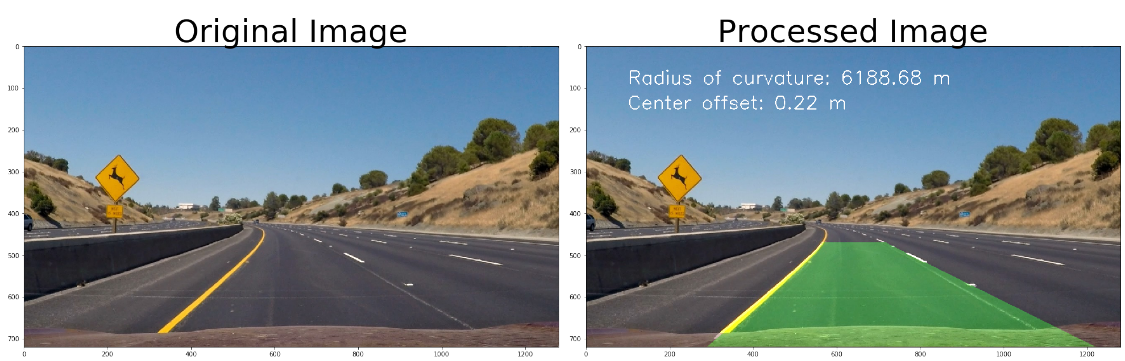
```
            else:
                mean_difference = np.mean(right_x_predictions - left_x_predictions)
                if (mean_difference < 0.7*running_mean_difference_between_lines or
                    bad_lines = True
                else:
                    bad_lines = False
    else:
        bad_lines = False

if bad_lines:
    polyfit_left = None
    polyfit_right = None
    if len(past_good_left_lines) == 0 and len(past_good_right_lines) == 0:
        return img
    else:
        left_x_predictions = past_good_left_lines[-1]
        right_x_predictions = past_good_right_lines[-1]
else:
    past_good_left_lines, left_x_predictions = get_averaged_line(past_good_left_lin
    past_good_right_lines, right_x_predictions = get_averaged_line(past_good_right_
    mean_difference = np.mean(right_x_predictions - left_x_predictions)
    running_mean_difference_between_lines = 0.9*running_mean_difference_between_lin

left_line_window = np.array(np.transpose(np.vstack([left_x_predictions, y_points]))
right_line_window = np.array(np.flipud(np.transpose(np.vstack([right_x_predictions,

# compute the radius of curvature
left_curve_rad = measure_radius_of_curvature(left_x_predictions)
right_curve_rad = measure_radius_of_curvature(right_x_predictions)
average_curve_rad = (left_curve_rad + right_curve_rad)/2
curvature_string = "Radius of curvature: %.2f m" % average_curve_rad

# compute the offset from the center
lane_center = (right_x_predictions[num_rows-1] + left_x_predictions[num_rows-1])/2
xm_per_pix = 3.7/700 # meters per pixel in x dimension
center_offset_pixels = abs(img_size[0]/2 - lane_center)
center_offset_mtrs = xm_per_pix*center_offset_pixels
offset_string = "Center offset: %.2f m" % center_offset_mtrs

poly_points = np.vstack([left_line_window, right_line_window])

cv2.fillPoly(out_img, np.int_([poly_points]), [0,255, 0])

unwarped = cv2.warpPerspective(out_img, M_inv, img_size , flags=cv2.INTER_LINEAR)

result = cv2.addWeighted(img, 1, unwarped, 0.3, 0)

cv2.putText(result,curvature_string , (100, 90), cv2.FONT_HERSHEY_SIMPLEX, 1.5, (25
```

```
    cv2.putText(result, offset_string, (100, 150), cv2.FONT_HERSHEY_SIMPLEX, 1.5, (255,

    return result
```

1.8 Step 7: Output visual display of the lane boundaries and numerical estimation of lane curvature and vehicle position.

The final step in processing the images was to plot the polynomials on to the warped image, fill the space between the polynomials to highlight the lane that the car is in, use another perspective trasformation to unwarp the image from birds eye back to its original perspective, and print the distance from center and radius of curvature on to the final annotated image.

```
In [16]: img = mpimg.imread('test_images/test2.jpg')

         # Reinitialize some global variables.
         polyfit_left = None
         polyfit_right = None
         past_good_right_lines = []
         past_good_left_lines = []
         running_mean_difference_between_lines = 0

         # Apply pipeline
         processed = pipeline_final(img)

         # Plot the 2 images
         f, (ax1, ax2) = plt.subplots(1, 2, figsize=(24, 9))
         f.tight_layout()
         ax1.imshow(img)
         ax1.set_title('Original Image', fontsize=50)
         ax2.imshow(processed, cmap='gray')
         ax2.set_title('Processed Image', fontsize=50)
         plt.subplots_adjust(left=0., right=1, top=0.9, bottom=0.)
```



1.9 Pipeline Video

We use moviepy to apply this pipeline to a video. Here is the link to the project video.

1.10 Youtube Link

Here is a link to the project video https://youtu.be/KC97lnt-REs

1.11 Pipeline Video: Challenge

We apply the pipeline on the challenge video. The challenge video has:

Shadows cast by the lane divider Lanes lines change color Brightness of the lanes varies throughout the video. The pipeline still works well on the challenge video.

1.11.1 Youtube link

Here is the link for the challenge video https://youtu.be/OE0gv118QRM

1.12 Pipeline Video: Harder Challenge

I applied the pipeline on the challenge video but brightness of the lanes varies too much throughout the video.

1.12.1 Youtube link

Here is the link for the challenge video https://youtu.be/vNbF4KSBo8Y

```
In [19]: from moviepy.editor import VideoFileClip

         # Reinitialize some global variables.
         polyfit_left = None
         polyfit_right = None
         past_good_right_lines = []
         past_good_left_lines = []
         running_mean_difference_between_lines = 0


         output = 'challenge_video_output.mp4'
         clip1 = VideoFileClip("challenge_video.mp4")
         white_clip = clip1.fl_image(pipeline_final) #NOTE: this function expects color images!!
         %time white_clip.write_videofile(output, audio=False)
```

```
[MoviePy] >>>> Building video challenge_video_output.mp4
[MoviePy] Writing video challenge_video_output.mp4


100%|| 485/485 [02:31<00:00,  3.15it/s]


[MoviePy] Done.
[MoviePy] >>>> Video ready: challenge_video_output.mp4

CPU times: user 1min 26s, sys: 18.8 s, total: 1min 45s
Wall time: 2min 34s
```

1.13 Discussion

1.13.1 Issues and Challenges

1.13.2 Gradient & Color Thresholding

I had to experiment a lot with gradient and color channnel thresholding. The lanes lines in the challenge and harder challenge videos were extremely difficult to detect. They were either too bright or too dull. This prompted me to have R & G channel thresholding and L channel thresholding

1.13.3 Bad Frames

The challenge video has a section where the car goes underneath a tunnel and no lanes are detected To tackle this I had to resort to averaging over the previous well detected frames The lanes in the challenge video change in color, shape and direction. I had to experiment with color threholds to tackle this. Ultimately I had to make use of R, G channels and L channel thresholds.

1.13.4 Points of failure & Areas of Improvement

The pipeline seems to fail for the harder challenge video. This video has sharper turns and at very short intervals.I think what I could improve is:

Take a better perspective transform: choose a smaller section to take the transform since this video has sharper turns and the lenght of a lane is shorter than the previous videos. Average over a smaller number of frames. Right now I am averaging over 12 frames. This fails for the harder challenge video since the shape and direction of lanes changes quite fast.