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 (https://review.udacity.com/#!/rubrics/571/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.

This is the Writeup / README file.

Camera Calibration

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

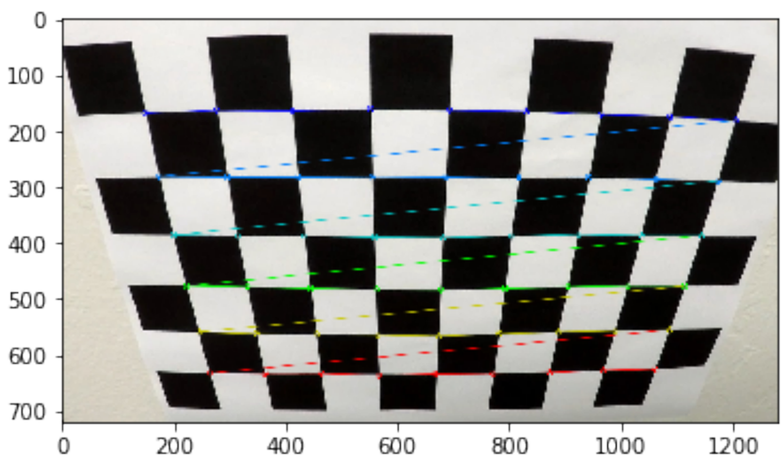
The code for this step is contained in the first code cell of the IPython notebook.

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.

In [1]:
```
import numpy as np
import cv2
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
from PIL import Image
from moviepy.editor import VideoFileClip
from IPython.display import HTML
%matplotlib inline
```

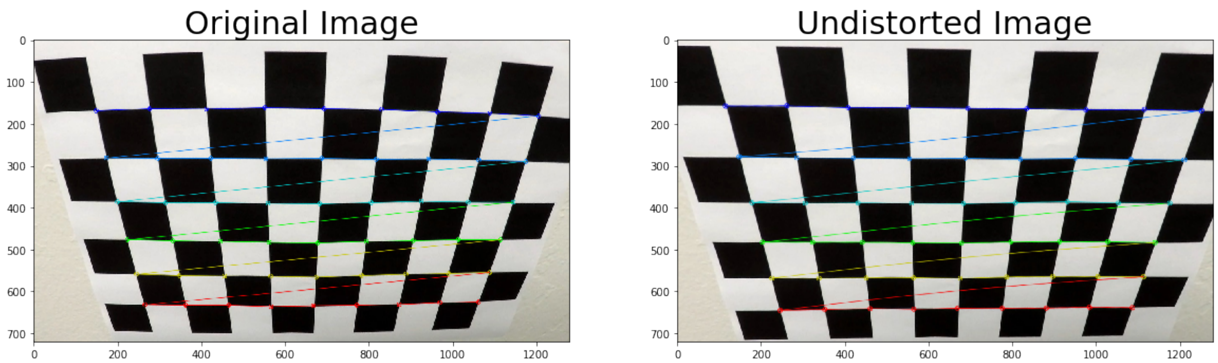
In [2]:
```
# Read in a calibration image
img = mpimg.imread('./camera_cal/calibration2.jpg')
plt.imshow(img)

# Arrays to store object points and image points from all the images

xPoints = 9
yPoints = 6

objpoints = [] # 3D points in real world space
imgpoints = [] # 2D points in image plane

# Prepare object points, like (0, 0, 0), (1, 0, 0), (2, 0, 0) ...,(7,
objp = np.zeros((yPoints*xPoints,3), np.float32)
objp[:,:2] = np.mgrid[0:xPoints, 0:yPoints].T.reshape(-1,2) #x,  y coo

# Convert image to grayscale
gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

# Find the chessboard corners
ret, corners = cv2.findChessboardCorners(gray, (xPoints, yPoints), Non

# If corners are found, add objectpoints, image points
if ret == True:

    imgpoints.append(corners)
    objpoints.append(objp)

    # draw and display the corners
    img = cv2.drawChessboardCorners(img, (xPoints, yPoints), corners,
    plt.imshow(img)
```



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:

In [3]:
```
import pickle
%matplotlib inline

# Test undistortion on an image
img_size = (img.shape[1], img.shape[0])

# Do camera calibration given object points and image points
ret, mtx, dist, rvecs, tvecs = cv2.calibrateCamera(objpoints, imgpoints

dst = cv2.undistort(img, mtx, dist, None, mtx)
cv2.imwrite('output_images/undist.jpg',dst)

# Save the camera calibration result for later use (we won't worry abo
dist_pickle = {}
dist_pickle["mtx"] = mtx
dist_pickle["dist"] = dist
pickle.dump( dist_pickle, open( "output_images/wide_dist_pickle.p", "wb
#dst = cv2.cvtColor(dst, cv2.COLOR_BGR2RGB)
# Visualize undistortion
f, (ax1, ax2) = plt.subplots(1, 2, figsize=(20,10))
ax1.imshow(img)
ax1.set_title('Original Image', fontsize=30)
ax2.imshow(dst)
ax2.set_title('Undistorted Image', fontsize=30)
```

Out[3]: <matplotlib.text.Text at 0x11e1c4358>



Pipeline (single images)

The pipeline will be organsied as follow: `process_image` is the overall pipeline function that will be used process the video.

Please note, the below cell have dependency on the 6 sections which contain the implementation detail of the functions.

In [17]:
```
src = np.float32(
    [[(img_size[0] / 2) - 60, img_size[1] / 2 + 100],
    [((img_size[0] / 6) - 10), img_size[1]],
    [(img_size[0] * 5 / 6) + 60, img_size[1]],
    [(img_size[0] / 2 + 65), img_size[1] / 2 + 100]])
dst = np.float32(
```

```
dst = np.float32(
    [[(img_size[0] / 4), 0],
    [(img_size[0] / 4), img_size[1]],
    [(img_size[0] * 3 / 4), img_size[1]],
    [(img_size[0] * 3 / 4), 0]])

def process_image(input_image):
    # Compute the camera calibration matrix and distortion coefficient

    # Apply a distortion correction to raw images.
    undist_img = undistort(input_image)

    # Use color transforms, gradients, etc., to create a thresholded b
    threshold_binary_image_tmp = threshold_binary(undist_img)

    # Apply a perspective transform to rectify binary image ("birds-ey
    perspective_transform_image_tmp = perspective_transform(threshold_l

    # Detect lane pixels and fit to find the lane boundary.
    left_fitx_tmp, right_fitx_tmp, ploty_tmp = prepare_for_plot(perspe

    # Determine the curvature of the lane and vehicle position with re
    left_curverad_tmp, right_curverad_tmp = curvature(left_fitx_tmp, r

    # Warp the detected lane boundaries back onto the original image.
    Minv_tmp = cv2.getPerspectiveTransform(dst, src)
    processed_image = draw_green_line(perspective_transform_image_tmp,

    # Output visual display of the lane boundaries and numerical estim

    return processed_image

# laneImage = mpimg.imread('./test_images/sampleTest.jpg')
laneImage = mpimg.imread('./test_images/test2.jpg')
processedImage = process_image(laneImage)

f, (ax1, ax2) = plt.subplots(1, 2, figsize=(20,10))
ax1.imshow(laneImage)
ax1.set_title('Original Image', fontsize=30)
ax2.imshow(processedImage)
ax2.set_title('Pipe Line Result Image', fontsize=30)
```

Out[17]: <matplotlib.text.Text at 0x11bcc1978>

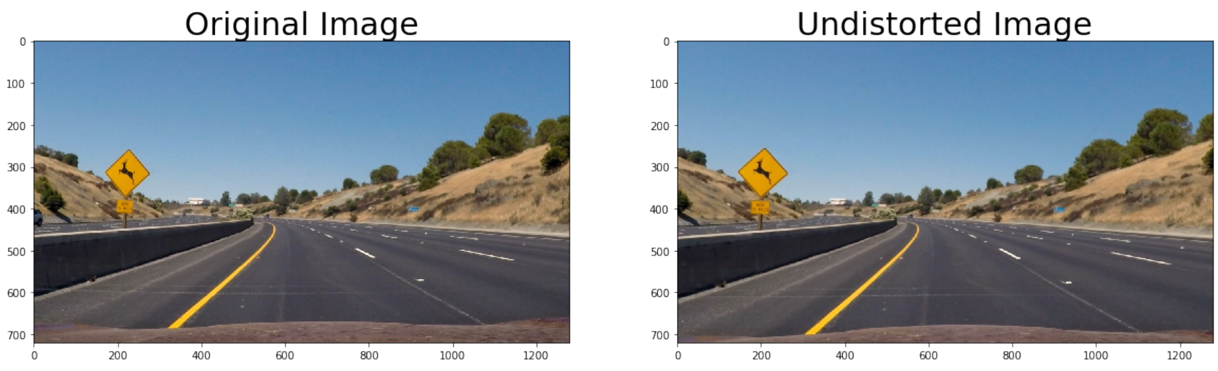
1. Provide an example of a distortion-corrected image.

To demonstrate this step, I will read the stored camera calibration from previous step, and then apply the correction to one of the test images like this one:

In [5]:
```
def undistort(image):
    with open("output_images/wide_dist_pickle.p", mode='rb') as f:
        dist_pickle = pickle.load(f)

    mtx = dist_pickle["mtx"]
    dist = dist_pickle["dist"]
    undist = cv2.undistort(image, mtx, dist, None, mtx)
    return undist
```

In [6]:
```
# laneImage = mpimg.imread('./test_images/sampleTest.jpg')
laneImage = mpimg.imread('./test_images/test2.jpg')

undistortImage = undistort(laneImage)

f, (ax1, ax2) = plt.subplots(1, 2, figsize=(20,10))
ax1.imshow(laneImage)
ax1.set_title('Original Image', fontsize=30)
ax2.imshow(undistortImage)
ax2.set_title('Undistorted Image', fontsize=30)

laneImage_undistort = cv2.cvtColor(undistortImage, cv2.COLOR_BGR2RGB)
cv2.imwrite('output_images/undist_laneImage.jpg', laneImage_undistort)
```

Out[6]: True



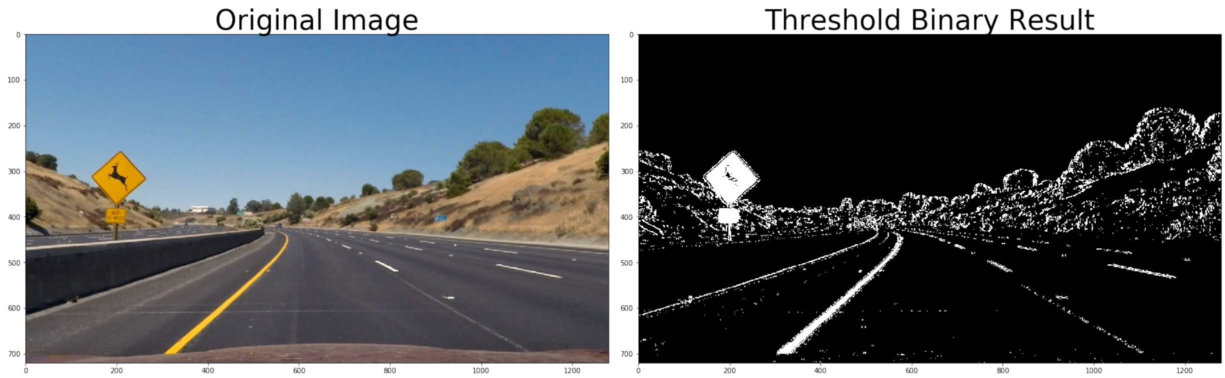
2. Describe how (and identify where in your code) you used color transforms, gradients or other methods to create a thresholded binary image. Provide an example of a binary image result.

I used a combination of color and gradient thresholds to generate a binary image (thresholding steps at below cell).

In [7]:
```
def threshold_binary(img, s_thresh=(170, 255), sx_thresh=(20, 100)):
    img = np.copy(img)
    # Convert to HSV color space and separate the V channel
    hls = cv2.cvtColor(img, cv2.COLOR_RGB2HLS)

    h_channel = hls[:,:,0]
    s_channel = hls[:,:,2]
    r_channel = img[:,:,0]
    # Sobel x

    sobelx = cv2.Sobel(r_channel, cv2.CV_64F, 1, 0) # Take the derivat
    abs_sobelx = np.absolute(sobelx) # Absolute x derivative to accent
    scaled_sobel = np.uint8(255*abs_sobelx/np.max(abs_sobelx))

    # Threshold x gradient
    sxbinary = np.zeros_like(scaled_sobel)
    sxbinary[(scaled_sobel >= sx_thresh[0]) & (scaled_sobel <= sx_thre

    # Threshold color channel
    s_binary = np.zeros_like(s_channel)
    s_binary[(s_channel >= s_thresh[0]) & (s_channel <= s_thresh[1])]

    # Threshold dir
    h_sobelx = cv2.Sobel(h_channel, cv2.CV_64F, 1, 0, ksize=5)
    h_sobely = cv2.Sobel(h_channel, cv2.CV_64F, 0, 1, ksize=5)

    absgraddir = np.arctan2(np.absolute(h_sobely), np.absolute(h_sobel
    h_binary =  np.zeros_like(absgraddir)
    h_binary[(absgraddir >= sx_thresh[0]) & (absgraddir <= sx_thresh[1

    # Stack each channel
    # Note color_binary[:, :, 0] is all 0s, effectively an all black i
    # be beneficial to replace this channel with something else.
    color_binary = np.dstack((h_binary, sxbinary, s_binary))

    # Combine the binary
    combined_binary = np.zeros_like(sxbinary)
    combined_binary[(h_binary == 1) | (s_binary == 1) | (sxbinary == 1
    return combined_binary
```

In [8]:

```
threshold_binary_image = threshold_binary(laneImage_undistort)

# Plot the result
f, (ax1, ax2) = plt.subplots(1, 2, figsize=(24, 9))
f.tight_layout()

ax1.imshow(undistortImage)
ax1.set_title('Original Image', fontsize=40)

ax2.imshow(threshold_binary_image, cmap='gray')
ax2.set_title('Threshold Binary Result', fontsize=40)
plt.subplots_adjust(left=0., right=1, top=0.9, bottom=0.)
```



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()` in the below cell. 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.float32(
    [[(img_size[0] / 2) - 60, img_size[1] / 2 + 100],
    [((img_size[0] / 6) - 10), img_size[1]],
    [(img_size[0] * 5 / 6) + 60, img_size[1]],
    [(img_size[0] / 2 + 60), img_size[1] / 2 + 100]])
dst = np.float32(
    [[(img_size[0] / 4), 0],
    [(img_size[0] / 4), img_size[1]],
    [(img_size[0] * 3 / 4), img_size[1]],
    [(img_size[0] * 3 / 4), 0]])
```

This resulted in the following source and destination points:

Source	Destination
580, 460	320, 0

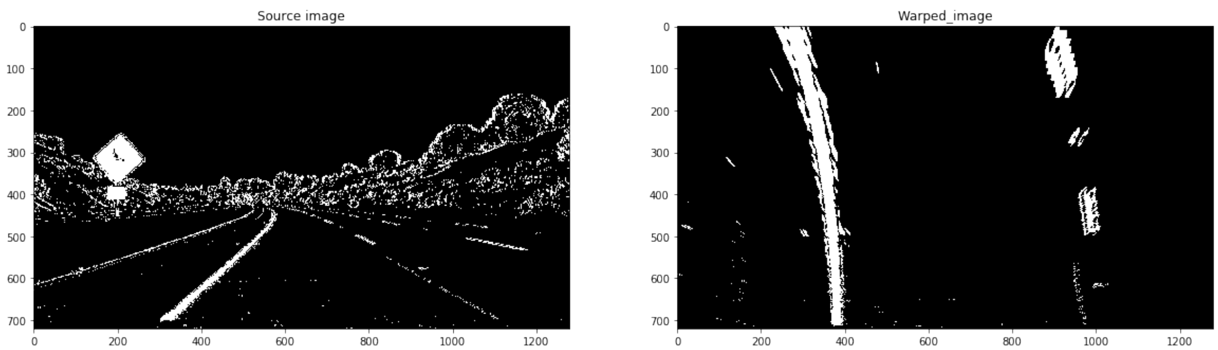
203, 720	320, 720
1127, 720	960, 720
700, 460	960, 0

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.

In [9]:
```
def perspective_transform(image, src, dst):
    img_size = (image.shape[1], image.shape[0])

    # Compute the perspective transform, M
    M = cv2.getPerspectiveTransform(src, dst)

    # Crate warped image - users liner interpolation
    return cv2.warpPerspective(image, M, img_size, flags=cv2.INTER_LIN
```

In [10]:
```

# Get perspective transform
perspective_transformed_image = perspective_transform(threshold_binary_

# Visulize undistortion
f, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 10))

ax1.set_title('Source image')
ax1.imshow(threshold_binary_image, cmap='gray')
ax2.set_title('Warped_image')
ax2.imshow(perspective_transformed_image, cmap='gray')

warped_output = cv2.cvtColor(perspective_transformed_image, cv2.COLOR_(
cv2.imwrite('./output_images/warped.jpg', warped_output)
```

Out[10]: True



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

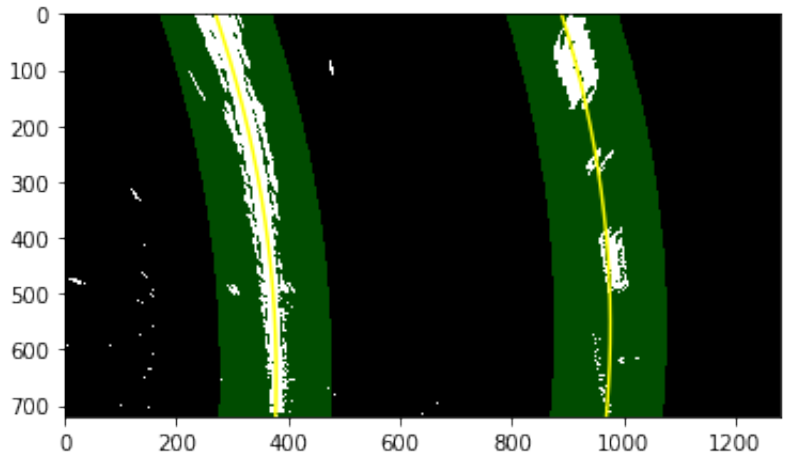
Then I calculated the pixel histogram, find the spike and find a 2nd order polynomial kinda like this:

In [11]:
```
window_width = 50
window_height = 80 # Break image into 9 vertical layers since image he
margin = 100 # How much to slide left and right for searching

def find_window_centroids(warped, window_width, window_height, margin)

    window_centroids = [] # Store the (left,right) window centroid pos
    window = np.ones(window_width) # Create our window template that w

    # First find the two starting positions for the left and right lan
    # and then np.convolve the vertical image slice with the window te

    # Sum quarter bottom of image to get slice, could use a different 
    l_sum = np.sum(warped[int(3*warped.shape[0]/4):,:int(warped.shape[
    l_center = np.argmax(np.convolve(window,l_sum))-window_width/2
    r_sum = np.sum(warped[int(3*warped.shape[0]/4):,int(warped.shape[1
    r_center = np.argmax(np.convolve(window,r_sum))-window_width/2+int

    # Add what we found for the first layer
    window_centroids.append((l_center,r_center))

    # Go through each layer looking for max pixel locations
    for level in range(1,(int)(warped.shape[0]/window_height)):
        # convolve the window into the vertical slice of the image
        image_layer = np.sum(warped[int(warped.shape[0]-(level+1)*wind
        conv_signal = np.convolve(window, image_layer)
        # Find the best left centroid by using past left center as a r
        # Use window_width/2 as offset because convolution signal refe
        offset = window_width/2
        l_min_index = int(max(l_center+offset-margin,0))
        l_max_index = int(min(l_center+offset+margin,warped.shape[1]))
        l_center = np.argmax(conv_signal[l_min_index:l_max_index])+l_m
        # Find the best right centroid by using past right center as a
        r_min_index = int(max(r_center+offset-margin,0))
        r_max_index = int(min(r_center+offset+margin,warped.shape[1]))
        r_center = np.argmax(conv_signal[r_min_index:r_max_index])+r_m
        # Add what we found for that layer
        window_centroids.append((l_center,r_center))

    return window_centroids

def get_window_centerY():
    return [680, 600, 520, 440, 360, 280, 200, 120, 40]

def prepare_for_plot(binary_warped):
    window_centroids = find_window_centroids(binary_warped, window_wid
    left_centerX, right_centerX = zip(*window_centroids)
    centerY = get_window_centerY()

    left_fit = np.polyfit(centerY, left_centerX, 2)
    right_fit = np.polyfit(centerY, right_centerX, 2)

    # Generate x and y values for plotting
```

```
    # Generate x and y values for plotting
    ploty = np.linspace(0, binary_warped.shape[0]-1, binary_warped.sha
    left_fitx = left_fit[0]*ploty**2 + left_fit[1]*ploty + left_fit[2]
    right_fitx = right_fit[0]*ploty**2 + right_fit[1]*ploty + right_fi
    return left_fitx, right_fitx, ploty
```

In [12]:

```
def display_plot(binary_warped, left_fitx, right_fitx, ploty):
    # Create an image to draw on and an image to show the selection wi
    out_img = np.dstack((binary_warped, binary_warped, binary_warped))
    window_img = np.zeros_like(out_img)


    # Generate a polygon to illustrate the search window area
    # And recast the x and y points into usable format for cv2.fillPol
    left_line_window1 = np.array([np.transpose(np.vstack([left_fitx-ma
    left_line_window2 = np.array([np.flipud(np.transpose(np.vstack([le
    left_line_pts = np.hstack((left_line_window1, left_line_window2))
    right_line_window1 = np.array([np.transpose(np.vstack([right_fitx-
    right_line_window2 = np.array([np.flipud(np.transpose(np.vstack([r
    right_line_pts = np.hstack((right_line_window1, right_line_window2

    # Draw the lane onto the warped blank image
    cv2.fillPoly(window_img, np.int_([left_line_pts]), (0,255, 0))
    cv2.fillPoly(window_img, np.int_([right_line_pts]), (0,255, 0))
    result = cv2.addWeighted(out_img, 1, window_img, 0.3, 0)
    plt.imshow(result)
    plt.plot(left_fitx, ploty, color='yellow')
    plt.plot(right_fitx, ploty, color='yellow')
    plt.xlim(0, 1280)
    plt.ylim(720, 0)

left_fitx, right_fitx, ploty = prepare_for_plot(perspective_transforme
display_plot(perspective_transformed_image, left_fitx, right_fitx, plo
```



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.

After I got the points on the line, then I use `curvature()` to calculte the curvature of the lane

In [13]:
```
def curvature(leftx, rightx, ploty):
    # Define conversions in x and y from pixels space to meters
    ym_per_pix = 30/720 # meters per pixel in y dimension
    xm_per_pix = 3.7/700 # meters per pixel in x dimension
    y_eval = np.max(ploty)

    # Fit new polynomials to x,y in world space
    left_fit_cr = np.polyfit(ploty*ym_per_pix, leftx*xm_per_pix, 2)
    right_fit_cr = np.polyfit(ploty*ym_per_pix, rightx*xm_per_pix, 2)
    # Calculate the new radii of curvature
    left_curverad = ((1 + (2*left_fit_cr[0]*y_eval*ym_per_pix + left_f
    right_curverad = ((1 + (2*right_fit_cr[0]*y_eval*ym_per_pix + righ
    # Now our radius of curvature is in meters

    return left_curverad, right_curverad
```

In [14]:
```
left_curv, right_curv = curvature(left_fitx, right_fitx, ploty)
print(left_curv,right_curv)

# Example values: 632.1 m    626.2 m
```

```
632.294640557 587.990308609
```

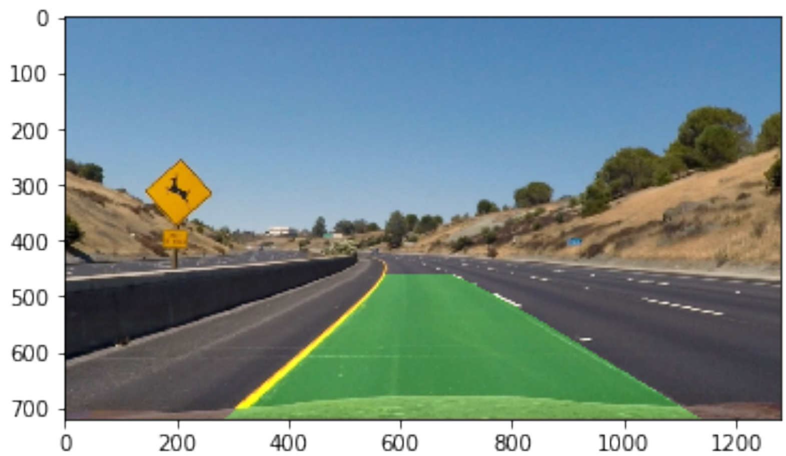
6. Provide an example image of your result plotted back down onto the road such that the lane area is identified clearly.

I use `draw_green_line()` to plot back the previous step on the image. Here is an example of my result on a test image:

In [15]:
```
def draw_green_line(warped, undist, Minv, left_fitx, right_fitx, ploty
    # Create an image to draw the lines on
    warp_zero = np.zeros_like(warped).astype(np.uint8)
    color_warp = np.dstack((warp_zero, warp_zero, warp_zero))

    # Recast the x and y points into usable format for cv2.fillPoly()
    pts_left = np.array([np.transpose(np.vstack([left_fitx, ploty]))])
    pts_right = np.array([np.flipud(np.transpose(np.vstack([right_fitx
    pts = np.hstack((pts_left, pts_right))

    # Draw the lane onto the warped blank image
    cv2.fillPoly(color_warp, np.int_([pts]), (0,255, 0))

    # Warp the blank back to original image space using inverse perspe
    newwarp = cv2.warpPerspective(color_warp, Minv, (undist.shape[1], 
    # Combine the result with the original image

    result = cv2.addWeighted(undist, 1, newwarp, 0.3, 0)

    return result
```

In [16]:
```
# Define a class to receive the characteristics of each line detection
class Line():
    def __init__(self):
        # was the line detected in the last iteration?
        self.detected = False
        # x values of the last n fits of the line
        self.recent_xfitted = []
        #average x values of the fitted line over the last n iteration
        self.bestx = None
        #polynomial coefficients averaged over the last n iterations
        self.best_fit = None
        #polynomial coefficients for the most recent fit
        self.current_fit = [np.array([False])]
        #radius of curvature of the line in some units
        self.radius_of_curvature = None
        #distance in meters of vehicle center from the line
        self.line_base_pos = None
        #difference in fit coefficients between last and new fits
        self.diffs = np.array([0,0,0], dtype='float')
        #x values for detected line pixels
        self.allx = None
        #y values for detected line pixels
        self.ally = None

Minv = cv2.getPerspectiveTransform(dst, src)
result = draw_green_line(perspective_transformed_image, undistortImage
plt.imshow(result)
```

Out[16]: <matplotlib.image.AxesImage at 0x11fd1e4e0>



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 (./project_video.mp4)](./project_video.mp4)

In [57]:
```
pipe_line_output = "pipeLineOutput.mp4"
clip1 = VideoFileClip("project_video.mp4")
pipe_line_output_clip = clip1.fl_image(process_image)
%time pipe_line_output_clip.write_videofile(pipe_line_output, audio=Fa
```

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

100%|██████████| 1260/1261 [03:33<00:00,  5.80it/s]

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

CPU times: user 4min 12s, sys: 39.4 s, total: 4min 52s
Wall time: 3min 34s
```

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?

During the observation, it seems the pipeline will fail from 22 - 24 seconds and 39 - 41 seconds where a different type of road will be presented.

There is a high chance for the yellow line being thresholded.

Potential rectification would be to implement memory based search and only search the lane line based on known lane line area.

In [ ]: