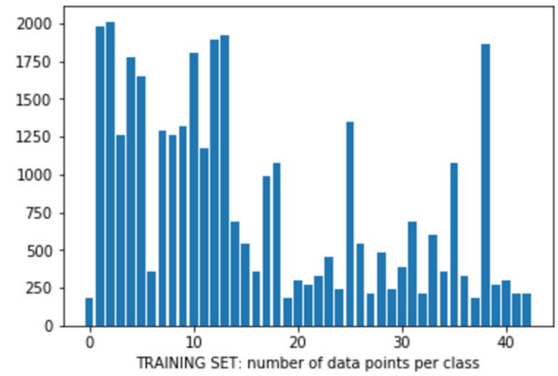
PROJECT 2: TRAFFIC SIGN CLASSIFIER USING DEEP LEARNING NEURAL NETWORK TECHNIQUES

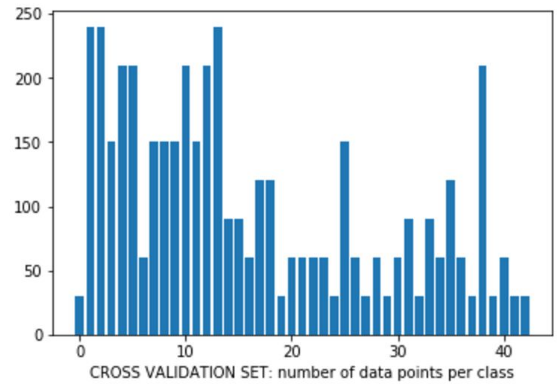
March 5, 2017 Shulamith Mithi Sevilla

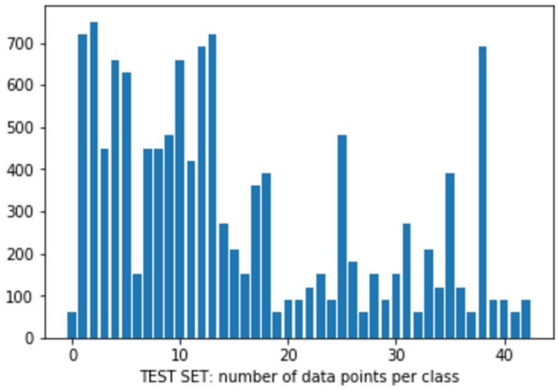
- Exploration of data
- Designing and testing the model architecture
- \- preprocessing techniques
- \- details about the neural network
- \- details about training the network
- Test on new images from the internet
- Appendix Images, Recommendation and References

EXPLORATION OF DATA

HISTOGRAMS







SEE APPENDIX FOR
A: 450 random images from the training set
B. 15 random images per classification (43 classifications)

BASIC STATISTICS

TRAINING DATA SET SIZE	**34799**
CROSS VALIDATION DATA SET SIZE	**4410**
TEST DATA SET SIZE	**12630**
IMAGE SHAPE	**32 x 32 x 3**
NUMBER OF LABELS	**43**

TOTAL INSTANCES	END COUNT	LABEL #	NAME
210	210	41	End of no passing
690	900	31	Wild animals crossing
330	1230	36	Go straight or right
540	1770	26	Traffic signals
450	2220	23	Slippery road
1980	4200	1	Speed limit (30km/h)
300	4500	40	Roundabout mandatory
330	4830	22	Bumpy road
180	5010	37	Go straight or left
360	5370	16	Vehicles over 3.5 metric tons prohibited
1260	6630	3	Speed limit (60km/h)
180	6810	19	Dangerous curve to the left
1770	8580	4	Speed limit (70km/h)
1170	9750	11	Right-of-way at the next intersection
210	9960	42	End of no passing by vehicles over 3.5 metric tons
180	10140	0	Speed limit (20km/h)
210	10350	32	End of all speed and passing limits
210	10560	27	Pedestrians
240	10800	29	Bicycles crossing
240	11040	24	Road narrows on the right
1320	12360	9	No passing
1650	14010	5	Speed limit (80km/h)
1860	15870	38	Keep right
1260	17130	8	Speed limit (120km/h)
1800	18930	10	No passing for vehicles over 3.5 metric tons
1080	20010	35	Ahead only
360	20370	34	Turn left ahead
1080	21450	18	General caution
360	21810	6	End of speed limit (80km/h)
1920	23730	13	Yield
1290	25020	7	Speed limit (100km/h)
390	25410	30	Beware of ice/snow
270	25680	39	Keep left
270	25950	21	Double curve
300	26250	20	Dangerous curve to the right
599	26849	33	Turn right ahead
480	27329	28	Children crossing
1890	29219	12	Priority road
690	29909	14	Stop
540	30449	15	No vehicles
990	31439	17	No entry
2010	33449	2	Speed limit (50km/h)
1350	34799	25	Road work

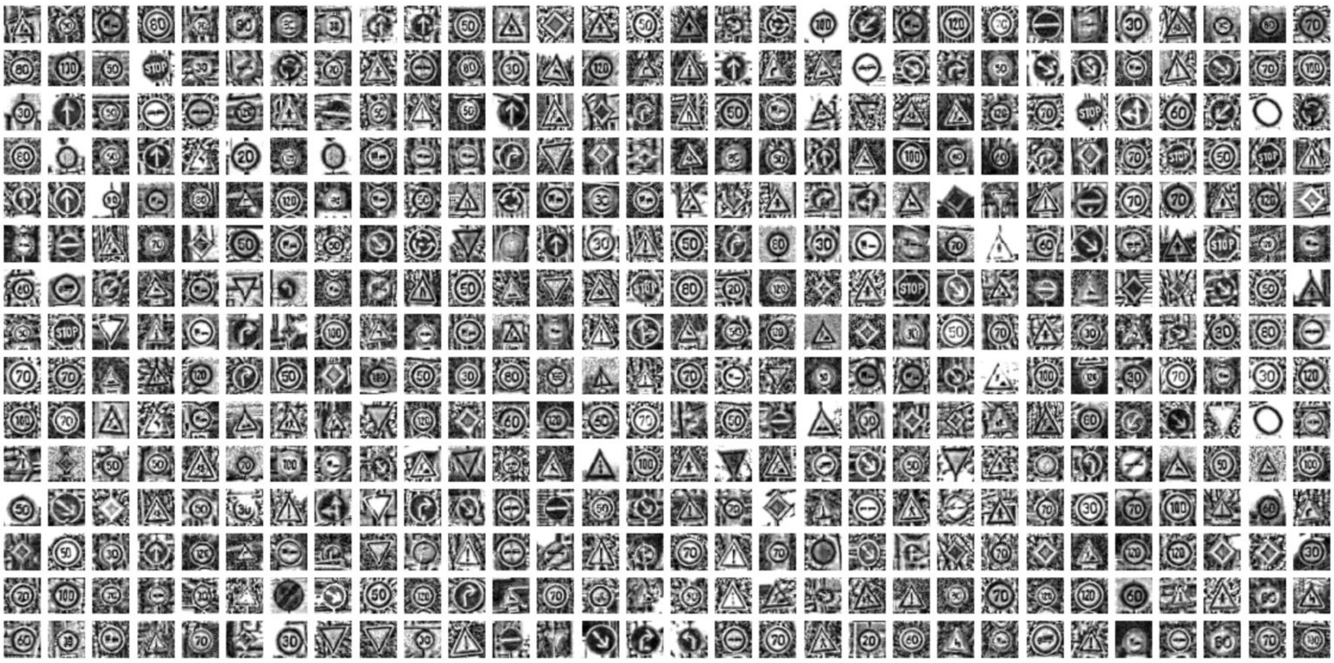
Datasets publicly available here -
http://benchmark.ini.rub.de/?section=gtsrb&subsection=dataset
https://d17h27t6h515a5.cloudfront.net/topher/2016/November/581faac4_traffic-signs-data/traffic-signs-data.zip

DESIGN AND TEST THE MODEL ARCHITECTURE

PREPROCESSING TECHNIQUES

- The images were first converted to grayscale.t ***Sermanet/LeCunn's pape***r (http://yann.lecun.com/exdb/publis/pdf/sermanet-ijcnn-11.pdf) talked about the lack of of increase in accuracy when color was used in classifying traffic signs. RGB color information was added information that would take longer to process by the neural network that would not increase accuracy so it is much better to just take this information out of the picture.
- A localized histogram equalization was applied because the images significantly differed in contrast and brightness.
- Values were scaled from [0, 255] to [0, 1]. We just this to easily ballpark the intensity of the pixel. This step is actually not necessary at all. It just looks nice.
- This algorithm and code was derived from the preprocessing techniques by Navoshta in his article: http://navoshta.com/traffic-signs-classification/

450 RANDOM PREPROCESSED IMAGES FROM THE TRAINING SET



DETAILS ABOUT THE NEURAL NETWORK

I used a simple model of two convolution layers followed by two fully connected layers. The two convolution layers both have a relu followed by a maxpool. The first fully connected layer had a relu, while the last layer did not. Below are more specifications of my neural network.

1st layer - Convolution	**2nd layer - Convolution**	**3rd layer - Fully Connected** (Wx + B)	**4th layer - Fully Connected** (Wx + B)
Filter_size = 5 x 5 Depth = 64 Stride = 1, padding = same Maxpool = 2x2 With Relu, No Dropout Output Size = 32 x 32 x depth	Filter_size = 5 x 5 Depth = 32 Stride = 1, padding = same Maxpool = 2x2 With Relu, No Dropout Output size = 16 x 16 x depth	(Flattened) With Relu With Dropout prob = 0.75 Output_size = 256	Dropout prob = 0.75 (no relu) Output_size = 43

- Of course the output of this in logits, so we feed this to a ***softmax*** function to get the probability and then feed that probability to a ***cross entropy*** function to convert it to a ***one hot encoding*** format.
- This architecture is a modified version of what was provided as an example in one of the lectures: *https://github.com/aymericdamien/TensorFlow-Examples/blob/master/examples/3_NeuralNetworks/convolutional_network.py*
- The parameters chosen here such as the **filter size, filter depth, output size,** are largely based on trial and error.
- A **padding** was chosen to be the **'same'** to keep the computation of the output matrix shape simple.
- The **maxpool** is used to prevent overfitting and decrease the size of the output (faster computations). A 2X2 maxpool with a stride of 1 as recommended in the lectures.
- **Dropouts** are added in the fully connected layer to help prevent overfitting.
- **Relu** functions are included to introduce nonlinearity to the system, and weed out the unnecessary negative values

DETAILS ABOUT HOW THE MODEL WAS TRAINED

A **learning rate of 0.00005**, **epoch of 180**, and **batch size** = **256 w**as chosen. The **adam optimizer** was chosen as recommended by the lectures.

I started with a higher learning rate but validation accuracy was going back and forth so I lowered it. The parameters are chosen largely from intuition and trial and error and also how the training was behaving based on the parameters. I stopped training when the validation accuracy was more than 95%, and the test accuracy was around 95% as well.

TESTING THE MODEL ON NEW IMAGES

I got 10 random german traffic sign images from the internet, and cropped them. I got 10 out of 10 signs predicted correctly. I think this is because I subconsciously chose the easiest ones to classify. All of them got at least 98% or more confidence except for the 2nd to the last image. Which is **Go straight or right.** This got an less than 90% confidence (89%) and got 7% confidence that it was seeing children crossing which was weird, because they really look different. It would be much understandable if it was mistaken to be an **ahead** sign. I think the reason for this is that the image was not cropped properly (It is leaning towards the right).

To strengthen the predictions of this neural network, I think we should feed it more data. Some of the classes were represented far more than others. The lack of balance in a data with result in a bias towards classes with more data points. We can generate more data points for less represented classes by applying small but random translational and rotational shifts as well as shearing and warping.

```
image_name = ['0-20speed','1-30speed', '12-priority-road','13-yield', '14-stop','17-no-entry',
              '18-general-caution','3-60speed', 36-go-straight-right', '40-roundabout-mandatory']

own_set_y = np.array([0, 1, 12, 13, 14, 17, 18, 3, 36, 40])

[ 0  1 12 13 14 17 18  3 36 40] <-predictions
 [ 0  1 12 13 14 17 18  3 36 40] <-actual
[[ 0  1 12 13 14 17 18  3 36 40]
 [ 1  2 35  5  3 33 26  6 28 11]
 [ 6  6 25 12  8  9 27  1 38 16]
 [29 38 26 33  1 14 24 34 35  7]
 [34  0 40  2  4 40 36 11 12 17]]
(top  5 predictions above) for each image

probability for top 5 predictions for each image:
0 [  9.32689548e-01   5.41089848e-02   1.31279845e-02   2.31403465e-05 1.45926260e-05]
1 [  9.99820888e-01   1.76206828e-04   1.00970851e-06   9.46819682e-07 7.42028533e-07]
2 [  1.00000000e+00   4.18683488e-09   7.02348402e-10   3.46118190e-10 3.12163795e-10]
3 [  1.00000000e+00   3.13466253e-10   2.64161998e-10   6.51305052e-11 3.08685751e-11]
4 [  9.99993563e-01   1.72575687e-06   1.65607423e-06   1.56471299e-06 9.00445173e-07]
5 [  1.00000000e+00   5.89572613e-10   1.53520793e-10   3.20257085e-11 2.61226735e-11]
6 [  1.00000000e+00   2.20382557e-09   8.86765050e-10   2.57165150e-10 1.40842324e-10]
7 [  9.99720633e-01   1.27843770e-04   7.89111946e-05   2.71247172e-05 2.42004371e-05]

9 [  1.00000000e+00   5.24315036e-09   4.45303838e-09   3.62437103e-09 2.18589946e-09]
Test Accuracy = 1.000
```

APPENDIX

RECOMMENDATIONS TO IMPROVE THIS DESIGN

- Augment the training set! Some of the classes were represented far more than others. The lack of balance in a data with result in a bias towards classes with more data points. We can generate more data points for less represented classes by applying small but random translational and rotational shifts as well as shearing and warping.
- Use L2 regulation techniques to prevent overfitting.
- Try fiddling with the filter size of the convolutional layers as well as its output/output depth, you can also fiddle with the output size of the fully connected layers and the dropout probability. AUGMENT AND BALANCE THE TRAINING DATA - Augmenting the training set might help improve model performance. ANALYZE NEW IMAGE PERFORMANCE IN MORE DETAIL -Calculating the accuracy on these five German traffic sign images found on the web might not give a comprehensive overview of how well the model is performing.
- CREATE VISUALIZATIONS OF THE SOFTMAX PROBABILITIES - For each of the five new images, create a graphic visualization of the soft-max probabilities. Bar charts might work well. VISUALIZE LAYERS OF THE NEURAL NETWORK
-

OTHER REFERENCES

http://yann.lecun.com/exdb/publis/pdf/sermanet-ijcnn-11.pdf
https://github.com/jeremy-shannon/CarND-Traffic-Sign-Classifier-Project
https://github.com/aymericdamien/TensorFlow-Examples/blob/master/examples/3_NeuralNetworks/convolutional_network.py
https://github.com/vxy10/p2-TrafficSigns
https://github.com/paramaggarwal/CarND-Traffic-Sign-Classifier-Project/blob/master/Traffic_Sign_Classifier.ipynb
https://github.com/MehdiSv/TrafficSignsRecognition/blob/master/final_Traffic_Signs_Recognition.ipynb
https://github.com/udacity/CarND-Traffic-Sign-Classifier-Project/blob/master/Traffic_Sign_Classifier.ipynb
https://github.com/navoshta/traffic-signs
https://github.com/hengck23-udacity/udacity-driverless-car-nd-p2

450 RANDOM IMAGES FROM THE TRAINING SET

15 RANDOM IMAGES PER CLASSIFICATIONS (43 CLASSIFICATIONS)