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Title: Leveraging GANs for Road Intersection Detection

Can you propose how to use generative adversarial networks to detect intersections on the road and eventually steer the car through driveway containing intersections?

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Introduction

cGAN

- M. Mirza and S. Osindero, “Conditional generative adversarial nets,” 2014, arXiv:1411.1784

Generative Adversarial Nets

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_z(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

Conditional Adversarial Nets

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x}|\boldsymbol{y})] + \mathbb{E}_{\boldsymbol{z}\sim p_z(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z}|\boldsymbol{y})))].$$

Experimental Setup

- Remove too small angles and too large angles
- For each angle, take no more than image_num_threshold images
- Replicate minority samples to alleviate the imbalance issue
- Normalize labels.

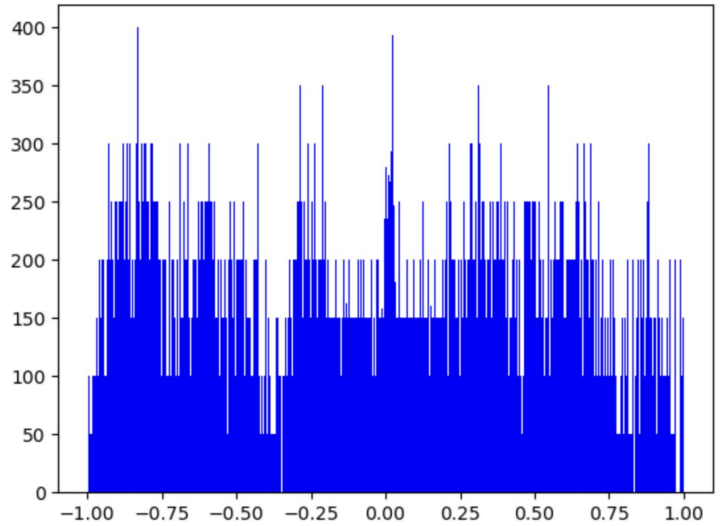


Fig 1. plot of normalized labels

Our Proposed framework

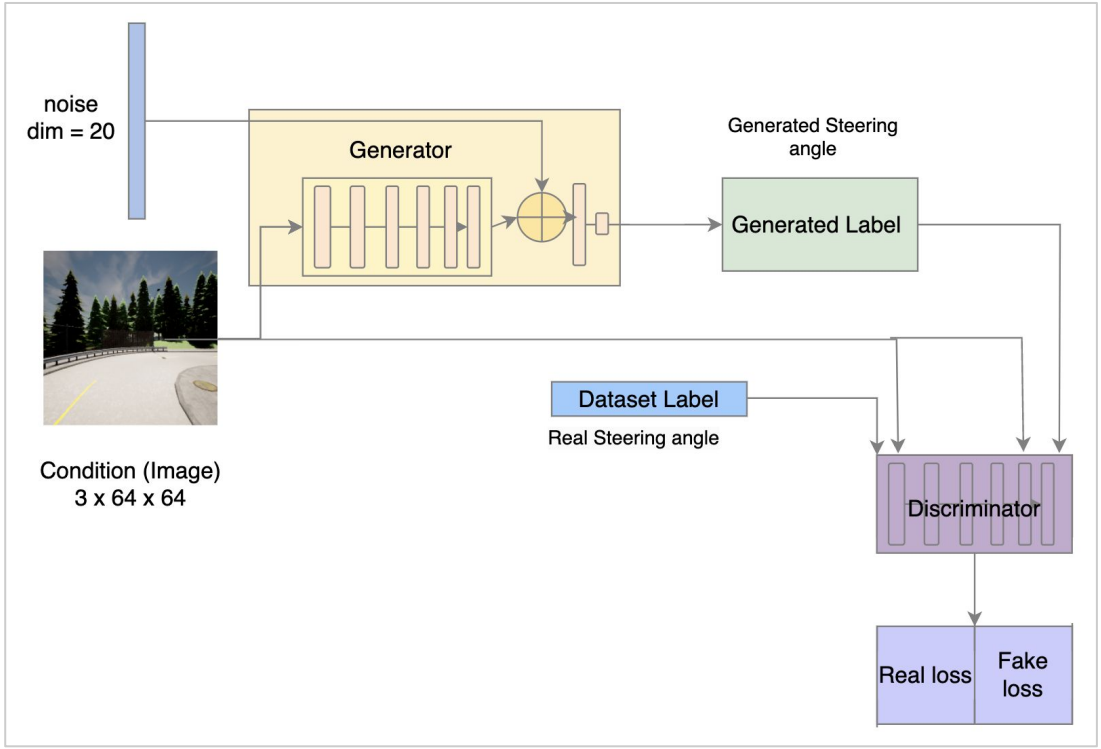
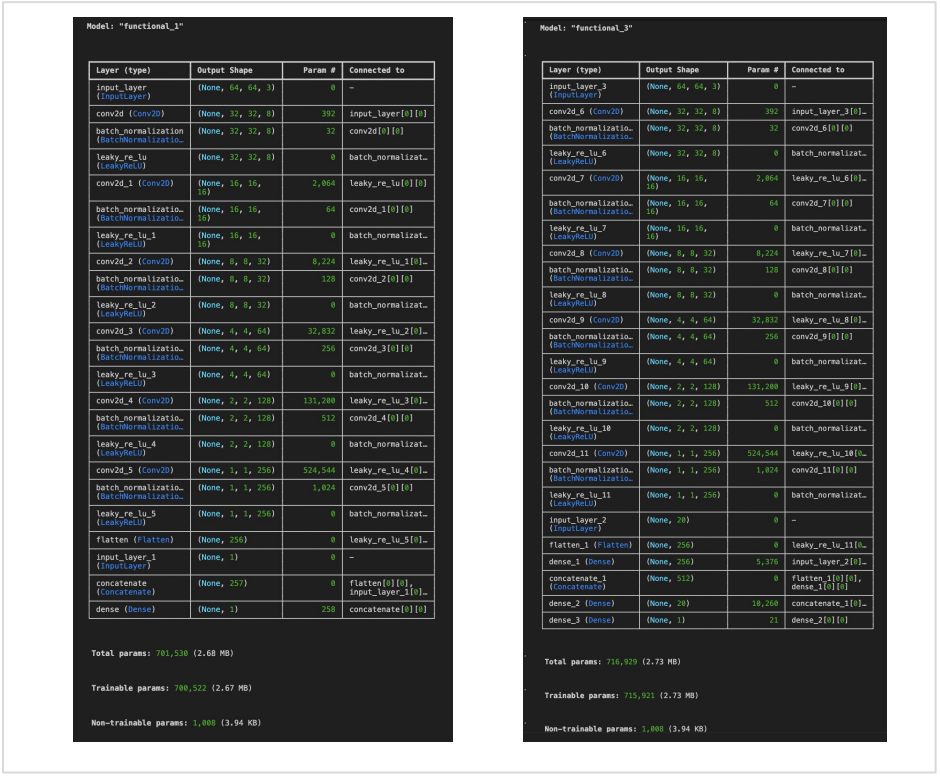


Fig 2: Model Architecture

Our Proposed framework



Model: "functional_1"

Layer (type)	Output Shape	Param #	Connected to
input_layer (InputLayer)	(None, 64, 64, 3)	0	-
conv2d (Conv2D)	(None, 32, 32, 8)	392	input_layer[0][0]
batch_normalization (BatchNormalizatio…	(None, 32, 32, 8)	32	conv2d[0][0]
leaky_re_lu (LeakyReLU)	(None, 32, 32, 8)	0	batch_normalizat…
conv2d_1 (Conv2D)	(None, 16, 16, 16)	2,064	leaky_re_lu[0][0]
batch_normalizatio… (BatchNormalizatio…	(None, 16, 16, 16)	64	conv2d_1[0][0]
leaky_re_lu_1 (LeakyReLU)	(None, 16, 16, 16)	0	batch_normalizat…
conv2d_2 (Conv2D)	(None, 8, 8, 32)	8,224	leaky_re_lu_1[0]…
batch_normalizatio… (BatchNormalizatio…	(None, 8, 8, 32)	128	conv2d_2[0][0]
leaky_re_lu_2 (LeakyReLU)	(None, 8, 8, 32)	0	batch_normalizat…
conv2d_3 (Conv2D)	(None, 4, 4, 64)	32,832	leaky_re_lu_2[0]…
batch_normalizatio… (BatchNormalizatio…	(None, 4, 4, 64)	256	conv2d_3[0][0]
leaky_re_lu_3 (LeakyReLU)	(None, 4, 4, 64)	0	batch_normalizat…
conv2d_4 (Conv2D)	(None, 2, 2, 128)	131,200	leaky_re_lu_3[0]…
batch_normalizatio… (BatchNormalizatio…	(None, 2, 2, 128)	512	conv2d_4[0][0]
leaky_re_lu_4 (LeakyReLU)	(None, 2, 2, 128)	0	batch_normalizat…
conv2d_5 (Conv2D)	(None, 1, 1, 256)	524,544	leaky_re_lu_4[0]…
batch_normalizatio… (BatchNormalizatio…	(None, 1, 1, 256)	1,024	conv2d_5[0][0]
leaky_re_lu_5 (LeakyReLU)	(None, 1, 1, 256)	0	batch_normalizat…
flatten (Flatten)	(None, 256)	0	leaky_re_lu_5[0]…
input_layer_1 (InputLayer)	(None, 1)	0	-
concatenate (Concatenate)	(None, 257)	0	flatten[0][0], input_layer_1[0]…
dense (Dense)	(None, 1)	258	concatenate[0][0]

Total params: 701,530 (2.68 MB)

Trainable params: 700,522 (2.67 MB)

Non-trainable params: 1,008 (3.94 KB)

Model: "functional_3"

Layer (type)	Output Shape	Param #	Connected to
input_layer_3 (InputLayer)	(None, 64, 64, 3)	0	-
conv2d_6 (Conv2D)	(None, 32, 32, 8)	392	input_layer_3[0]…
batch_normalizatio… (BatchNormalizatio…	(None, 32, 32, 8)	32	conv2d_6[0][0]
leaky_re_lu_6 (LeakyReLU)	(None, 32, 32, 8)	0	batch_normalizat…
conv2d_7 (Conv2D)	(None, 16, 16, 16)	2,064	leaky_re_lu_6[0]…
batch_normalizatio… (BatchNormalizatio…	(None, 16, 16, 16)	64	conv2d_7[0][0]
leaky_re_lu_7 (LeakyReLU)	(None, 16, 16, 16)	0	batch_normalizat…
conv2d_8 (Conv2D)	(None, 8, 8, 32)	8,224	leaky_re_lu_7[0]…
batch_normalizatio… (BatchNormalizatio…	(None, 8, 8, 32)	128	conv2d_8[0][0]
leaky_re_lu_8 (LeakyReLU)	(None, 8, 8, 32)	0	batch_normalizat…
conv2d_9 (Conv2D)	(None, 4, 4, 64)	32,832	leaky_re_lu_8[0]…
batch_normalizatio… (BatchNormalizatio…	(None, 4, 4, 64)	256	conv2d_9[0][0]
leaky_re_lu_9 (LeakyReLU)	(None, 4, 4, 64)	0	batch_normalizat…
conv2d_10 (Conv2D)	(None, 2, 2, 128)	131,200	leaky_re_lu_9[0]…
batch_normalizatio… (BatchNormalizatio…	(None, 2, 2, 128)	512	conv2d_10[0][0]
leaky_re_lu_10 (LeakyReLU)	(None, 2, 2, 128)	0	batch_normalizat…
conv2d_11 (Conv2D)	(None, 1, 1, 256)	524,544	leaky_re_lu_10[0…
batch_normalizatio… (BatchNormalizatio…	(None, 1, 1, 256)	1,024	conv2d_11[0][0]
leaky_re_lu_11 (LeakyReLU)	(None, 1, 1, 256)	0	batch_normalizat…
input_layer_2 (InputLayer)	(None, 20)	0	-
flatten_1 (Flatten)	(None, 256)	0	leaky_re_lu_11[0…
dense_1 (Dense)	(None, 256)	5,376	input_layer_2[0]…
concatenate_1 (Concatenate)	(None, 512)	0	flatten_1[0][0], dense_1[0][0]
dense_2 (Dense)	(None, 20)	10,260	concatenate_1[0]…
dense_3 (Dense)	(None, 1)	21	dense_2[0][0]

Total params: 716,929 (2.73 MB)

Trainable params: 715,921 (2.73 MB)

Non-trainable params: 1,008 (3.94 KB)

Fig 3: Discriminator and Generator

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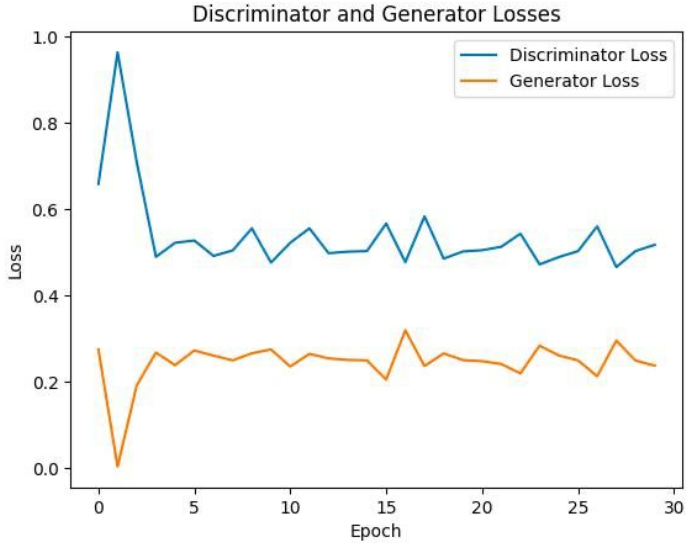
cGAN Framework

- CGAN framework implemented for a regression task, using Images as conditioning information for the generator.
- Training involved feeding both noise and Image as inputs to the generator, while the discriminator was also conditioned on the Image to distinguish between real and fake steering angles.
- Adam optimizer utilized with a batch size of 600, accompanied by a learning rate scheduler starting from 2e-4 with beta value 0.5.

Results and Observations



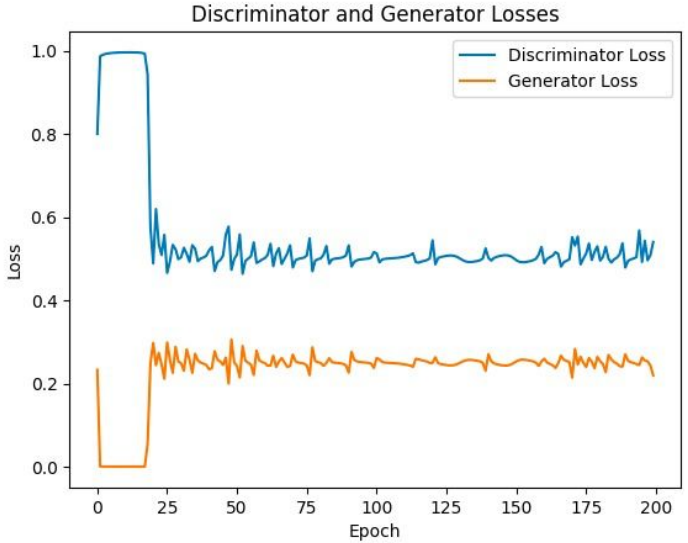


Fig 3 : Loss graph

Results and Conclusion

Steering Value: [0.39369476], Prediction: [0.47111893]

Steering Value: [-0.00262786], Prediction: [-0.09399101]

Steering Value: [0.35761097], Prediction: [0.7823007]

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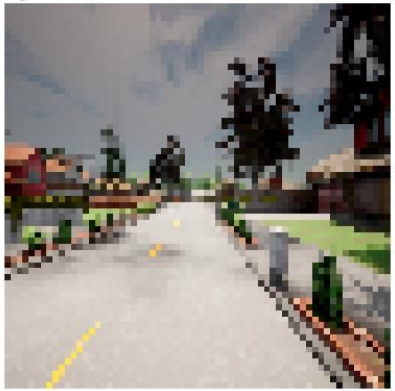
Results and Conclusion

Steering Value: [-0.00268138], Prediction: [-0.03222457]

Steering Value: [-0.0062463], Prediction: [-0.04826191]



Steering Value: [0.4089193], Prediction: [0.75929344]

```
Mean Absolute Error (MAE): 0.8700878510395419
Standard Deviation: 0.6885516226660812
Variance: 0.4741033370760934
Mean Squared Error (MSE): 0.7574108999654883
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Future Scope

Vicinal Risk Minimization

- Olivier Chapelle, Jason Weston, Leon Bottou, and Vladimir Vapnik. Vicinal risk minimization. In ´ Advances in neural information processing systems, pp. 416–422, 2001.
- X. Ding, Y. Wang, Z. Xu, W. J. Welch and Z. J. Wang, "Continuous Conditional Generative Adversarial Networks: Novel Empirical Losses and Label Input Mechanisms," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 45, no. 7, pp. 8143-8158, 1 July 2023, doi: 10.1109/TPAMI.2022.3228915.

$$\text{VRM Loss} = \frac{1}{|X|} \sum_{x_i \in X} \left(\frac{1}{|N(x_i)|} \sum_{x_j \in N(x_i)} |\hat{y}_i - \hat{y}_j| \right)$$

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References

- X. Ding, Y. Wang, Z. Xu, W. J. Welch and Z. J. Wang, "Continuous Conditional Generative Adversarial Networks: Novel Empirical Losses and Label Input Mechanisms," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 45, no. 7, pp. 8143-8158, 1 July 2023, doi: 10.1109/TPAMI.2022.3228915.
- X. Ding, Y. Wang, Z. Xu, W. J. Welch and Z. J. Wang, "Continuous Conditional Generative Adversarial Networks: Novel Empirical Losses and Label Input Mechanisms," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 45, no. 7, pp. 8143-8158, 1 July 2023, doi: 10.1109/TPAMI.2022.3228915.
- Olivier Chapelle, Jason Weston, Leon Bottou, and Vladimir Vapnik. Vicinal risk minimization. In ´ Advances in neural information processing systems, pp. 416–422, 2001.
- X. Ding, Y. Wang, Z. Xu, W. J. Welch and Z. J. Wang, "Continuous Conditional Generative Adversarial Networks: Novel Empirical Losses and Label Input Mechanisms," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 45, no. 7, pp. 8143-8158, 1 July 2023, doi: 10.1109/TPAMI.2022.3228915.
- S. Chen, “The Steering Angle dataset @ONLINE,” 2018. [Online].Available: https://github.com/SullyChen/driving-datasets

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THANK YOU