Attribute-Controlled Traffic Data Augmentation Using Conditional Generative Models

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Motivation

- Perception systems of self driving vehicles need to be robust against adverse light and weather conditions.
- Collection and annotation of such traffic data is resource intensive and expensive.

Traffic datasets are imbalanced which do not exhibit even distribution of data points across different weather and time of day attributes.

Checkpoints

- Train attribute-based generative models conditioned on time-of-day labels with image crops preprocessed from [Yu+18] dataset.
- Generate synthetic traffic data by flipping single valued attribute (day $\Longleftrightarrow$ night)
- Interpolate images with varying attribute values to demonstrate variation in intensities of the flipped attribute.

Trained model demonstrates examples of generalizability where it was able to reconstruct full traffic images with the flipped attribute.

Attribute GAN

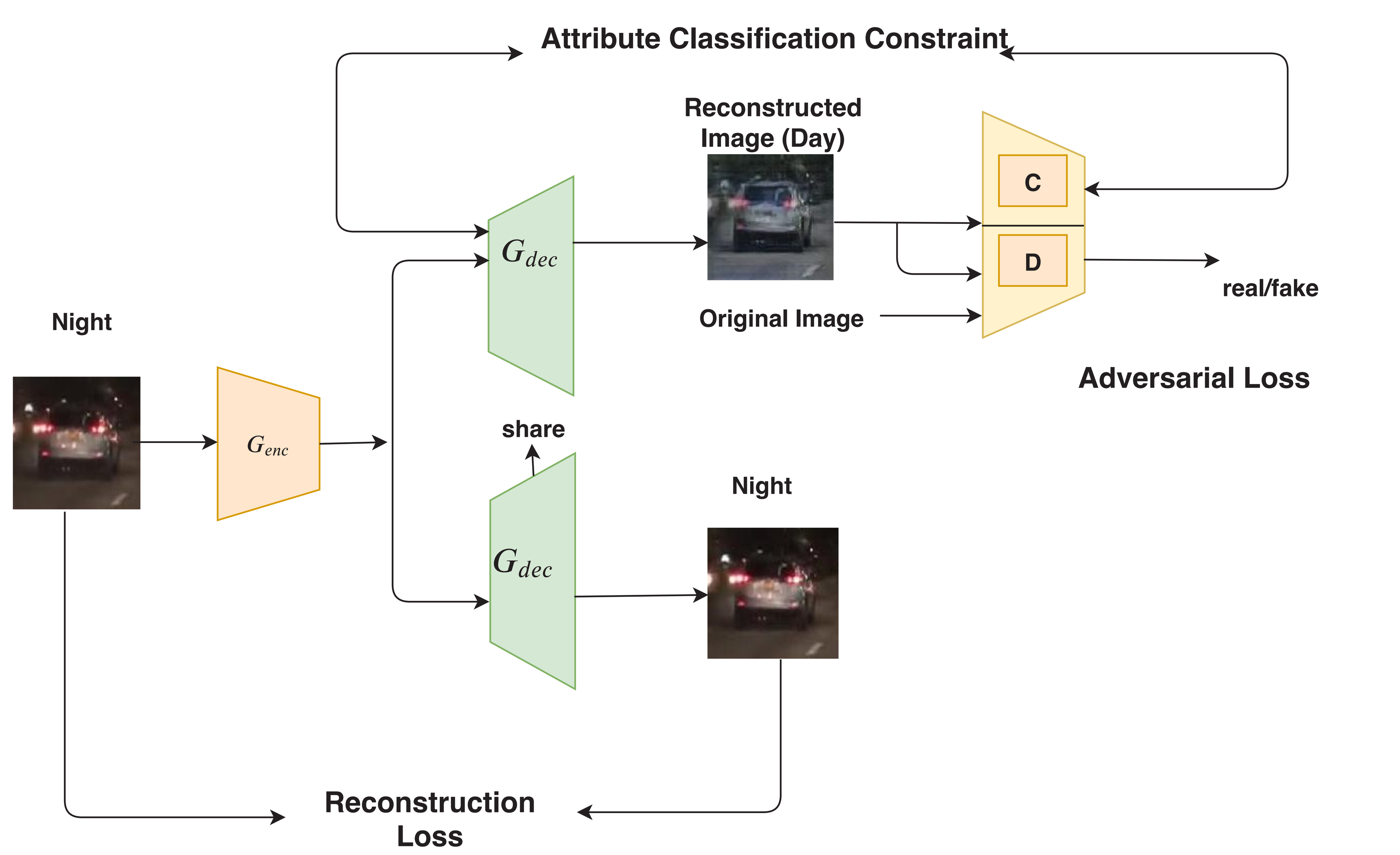

Fig. 1: *Block Diagram for time-of-the-day attribute flip.*

- Encoder Decoder architecture which uses a discriminator and classifier pair to analyse the reconstructed images with the desired flipped attribute.
- Optimizes over a reconstruction loss, an adversarial loss and an attribute constraint loss to ensure proper editing of desired attributes.
- While decoding decouples semantic attributes from the underlying identity data.

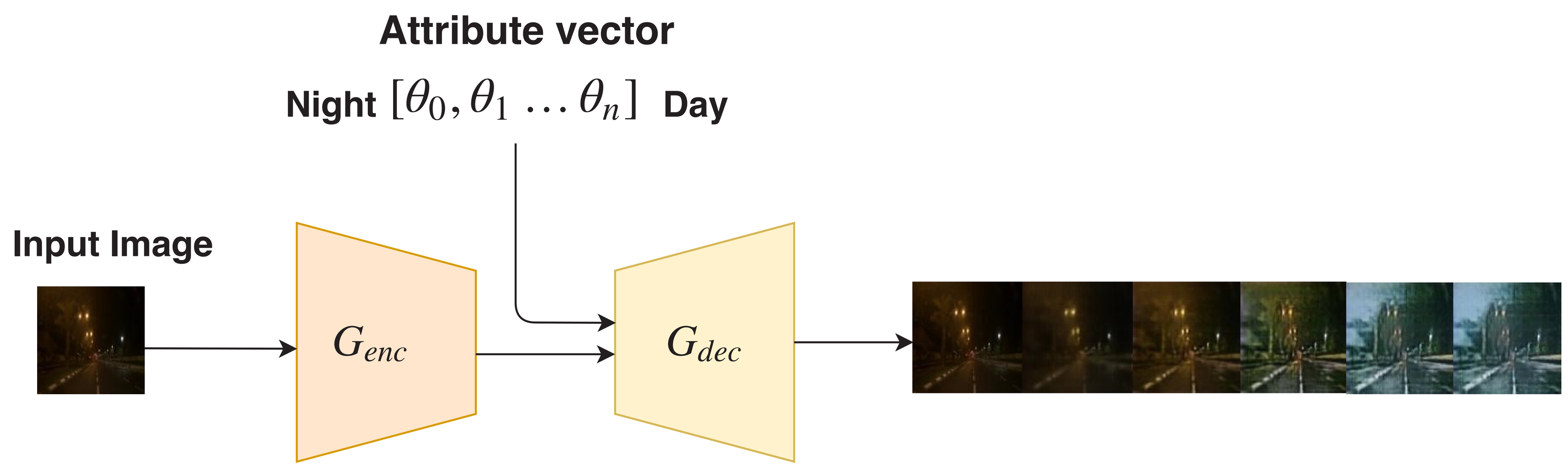

Fig. 2: *Block Diagram for interpolation on the time-of-the-day attribute.*

References

F. Yu *et al.*, "Bdd100k: A diverse driving video database with scalable annotation tooling", *arXiv preprint arXiv:1805.04687*, 2018.

Z. He *et al.*, "Attgan: Facial attribute editing by only changing what you want", *arxiv preprint arXiv:1711.10678*, 2017.

Preprocessing

Introduce a non-traditional approach to fairly represent a subset of the entire dataset to train an AttGAN [He+17]:

- Segment the dataset on the time of the day label into two classes : Day and Night.
- Crop objects of important classes (cars and traffic signs) using the 2D box annotations provided from the original dataset conditioned on the two labels.
- Constrain each image crop within an aspect ratio of 4:3 to prevent unnatural sheer while resizing before training.
- Increase the size of each image crop by 30 pixels on either sides than the provided box annotations so that day/night effects are perceptible.

Fig. 3: *Examples of images from the BDD++ dataset.*

Results

Fig. 4: *Semantically transformed images. (Left) Original Images (Center) Reconstructed images with the original attribute (Right) Reconstructed images with flipped attributes.*

Fig. 5: *Interpolated images on the time-of-day attribute.*

Attributes	Day		Night	
	Original	Generated	Original	Generated
Cars	54563	19178	19178	54563
Traffic Signs	7358	5003	5003	7358

Table 1: *Dataset distribution for BDD++.*