The conditional adversarial networks applied in existing works mainly consists of two parts: 1) the encoding-decoding nets (ED) and 2) the GANs, which are tied in the parts of decoder and generator. Therefore, the reconstruction loss and adversarial loss interact/compete with each other, while potentially causes unstable results as shown in the follow.

Existing works have to introduce a weighting factor (e.g., the values in the figure) to balance the effect of the two losses. How to adaptively set an appropriate weight or completely remove the necessity of the weighting factor is a problem unexplored.

**Motivation:**
The conditional adversarial networks applied in existing works mainly consists of two parts: 1) the encoding-decoding nets (ED) and 2) the GANs, which are tied in the parts of decoder and generator. Therefore, the reconstruction loss and adversarial loss interact/compete with each other, while potentially causes unstable results as shown in the follow.

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**Main Idea:**
Decouple the interaction between the reconstruction loss and adversarial loss in backpropagation, avoiding the competition that may cause instability.

- ED+GAN: the traditional structure
- ED//GAN: the proposed structure(decoupled learning)
- Enc and Dec: the encoder and decoder networks
- G and D: the generator and discriminator
- Black arrows: feedforward path
- Red arrows: backpropagation of reconstruction loss
- Blue arrows: backpropagation of adversarial loss

**Approach:**

\[
\mathcal{L}_{const}(Enc, Dec) = \| I - Dec(Enc(I)) \|_1
\]

Adversarial loss:

\[
\mathcal{L}_{adv}(D) = \mathbb{E} \left[ \log (1 - D(I)) \right] + \mathbb{E} \left[ \log D(IE_D + I_G) \right],
\]

\[
\mathcal{L}_{adv}(G) = \mathbb{E} \left[ \log (1 - D(IE_D + G(z))) \right],
\]

where \( I_{ED} = Dec(z) \) and \( z = Enc(I) \).

The objective function:

Above all, the objective function of the proposed decoupled learning (ED/GAN) is

\[
\min_{Enc, Dec} \mathcal{L}_{const}(Enc, Dec) + \min_G \mathcal{L}_{adv}(G) + \min_D \mathcal{L}_{adv}(D).
\]

Note that there are no weighting parameters between the losses in the objective function, which relaxes the manual tuning that may require an expert with strong domain knowledge and rich experience. During training, each component could be updated alternatively and independently because the three components do not overlap in backpropagation.

**Visualizing the Boost from Adversarial Learning:**

Left: output from ED. Middle: output from G (trained by the adversarial loss). Right: the final out of ED//GAN, adding the output from G to that from ED.