Domain Adaptation Meets Disentangled Representation Learning and Style Transfer

1 Idea

The authors intend to learn both common and specific representations of distinct handwriting styles, and then:

- Use the common styles for domain adaptation.
- Use the specific styles for style transfer.

2 Background

3 Method

- The data set comprises of source images S, target images T, and a set of labels for only the source images Y_S.
- The general idea is to learn the representations of S_C (content of source), S_S (style of source) and similarly, T_C and T_S for the target respectively.
- Semantic consistency and entropy are the two metrics that are used to bring the content representations together into the same distribution.
- F_S and F_T are both feature extractors that try to disambiguate style from content.

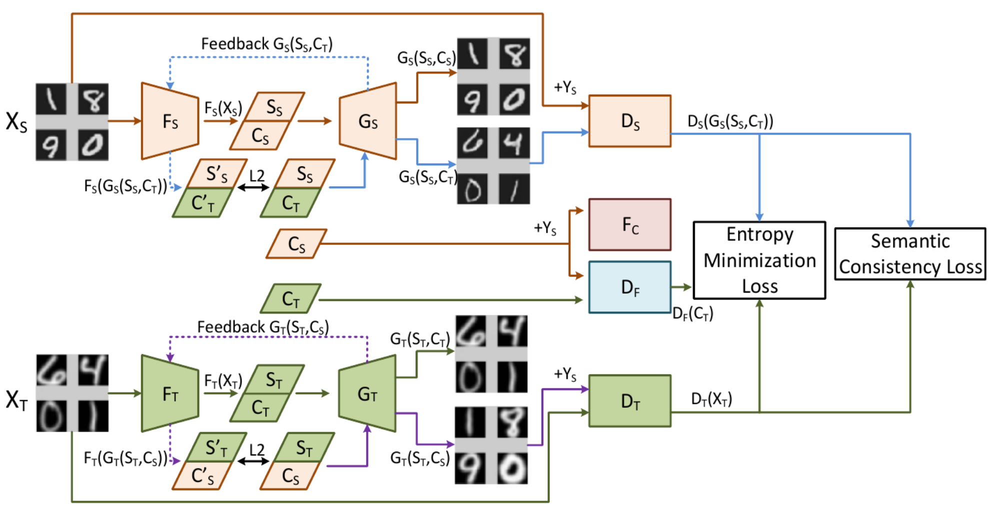
- The generators G_S and G_T are given the style of their respective networks with content from both the source and target sets. The idea is to train them such that it is encouraged by the network to maintain separation of responsibilities between the style components S and the content components C.

- D_F is the adversarial component that tries to distinguish between C_S and C_T, which the main network tries to make indistinguishable.

- F_C is a standard classifier that needs to be well trained on the supervised source data X_S and corresponding labels Y_S.

- The source discriminator D_S and the target discriminator D_T both try to predict which among the real source image and the style-transferred image is the real deal.

4 Architecture



5 Observations

- The interesting aspect is the transfer learning of the labels done via cross-alignment of the two data sets.

- The closest comparison I could derive in NLP would be to learn paraphrases of sentences by stripping each of style and relying only on the content information in C_S and C_T for comparison.