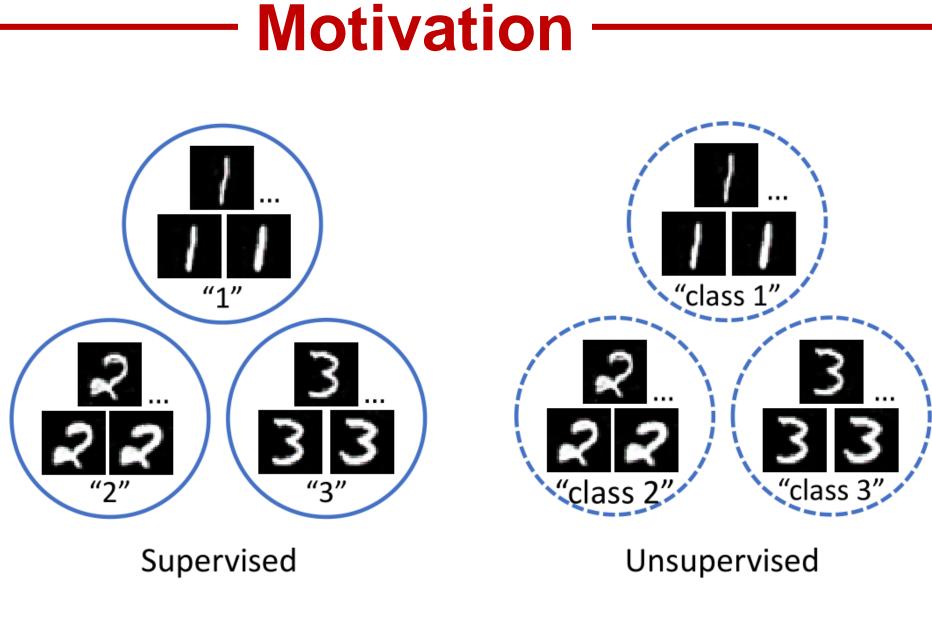


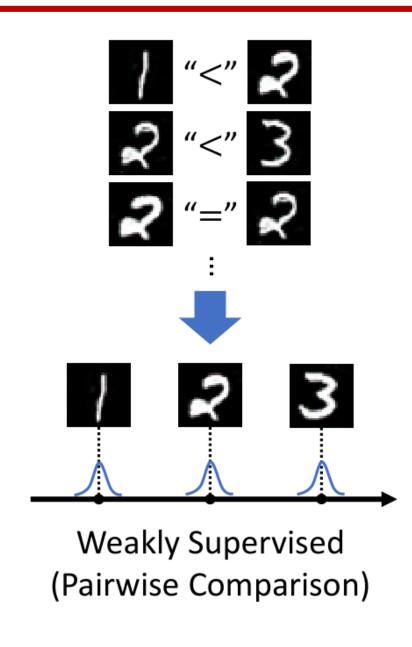
Robust Conditional GAN from Uncertainty-Aware Pairwise Comparisons

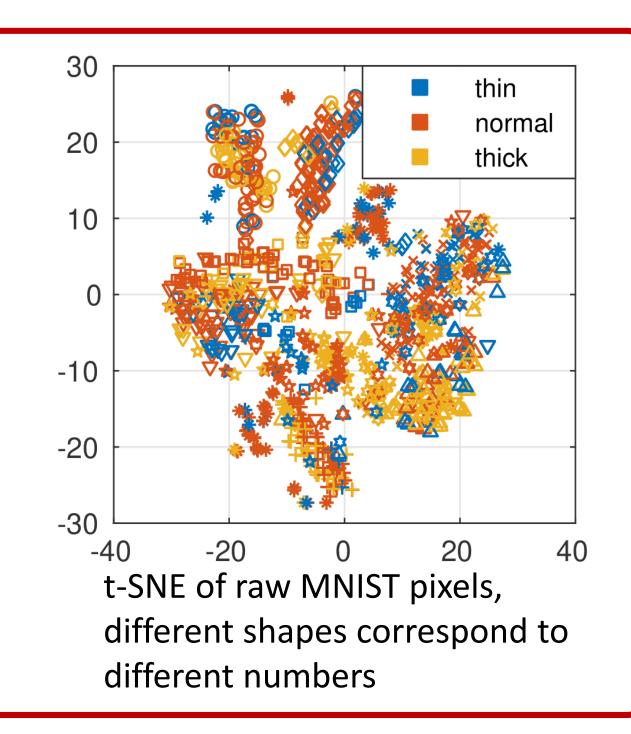
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- Traditional conditional GANs require many labeled data
- Unsupervised conditional GANs leverage unsupervised or self-supervised learning methods to obtain pseudo-labels
- For continuous-valued attributes or attributes that are NOT salient, e.g. stroke thickness of MNIST digits
- We consider *weak supervisions* in the form of pairwise comparisons







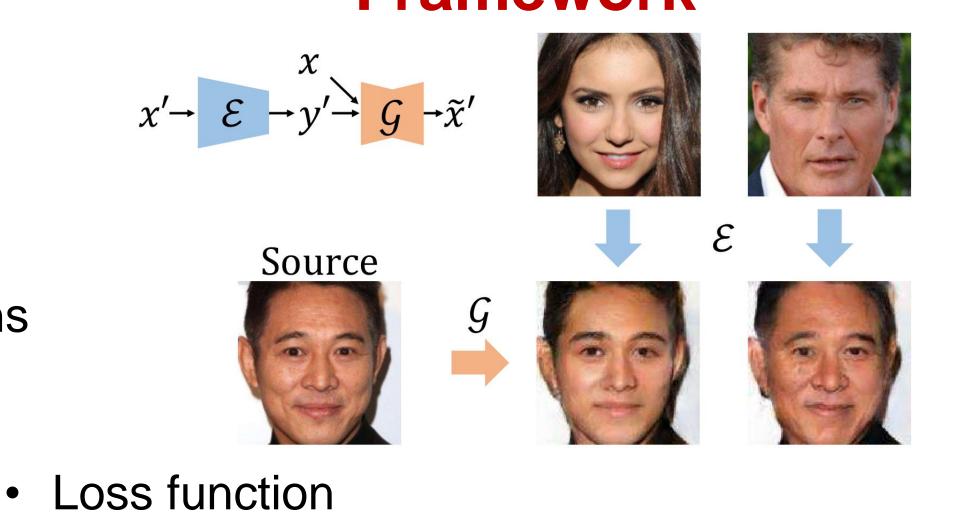
Framework

Generative Process

- Substitute the full supervision with the attribute ratings learned from weak supervisions
- Elo rating network with uncertainty estimations: learning intrinsic scores from pairwise comparisons
- Uncertainty-aware noise-robust conditional GANs

Elo Rating Network

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• Elo rating system (Elo 1978)
                                              P_A = \frac{1}{1 + 10^{(y_B - y_A)/400}}
                                              y'_A = \overline{y_A} + \overline{K}(S_A - P_A)
      P_A is the predicted probability of Player A
      winning the game, S_A is the actual score obtained
     x_{A} \rightarrow \underbrace{\mathcal{E}}_{\sigma_{A}} \sim y_{A} \xrightarrow{} \underbrace{\Omega(x_{A}) > \Omega(x_{B})}_{\text{sigm}} \qquad \underbrace{\Omega(x_{A}) > \Omega(x_{B})}_{\Omega(x_{A}) = \Omega(x_{B})}
x_{B} \rightarrow \underbrace{\mathcal{E}}_{\sigma_{B}} \sim y_{B} \xrightarrow{} \underbrace{\gamma_{B}}_{\text{sigm}} \quad \underbrace{\Omega(x_{A}) > \Omega(x_{B})}_{\Omega(x_{A}) < \Omega(x_{B})}
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 $P_A(\Omega(x_A) > \Omega(x_B)|x_A, x_B) = \int \operatorname{sigm}(y_A - y_B) dy_A dy_B$

 $\left| \mathcal{L}_{rank}^{UB} = -\mathbb{E}_{x_A, x_B \sim C} \right| \frac{1}{M} \sum_{m=1}^{M} S_A \log P_{A,y} + S_B \log P_{B,y} \right|$

 $\mathcal{L}_{rank}^{MC} = -\mathbb{E}_{x_A, x_B \sim C} \left[S_A \log P_A^{MC} + S_B \log P_B^{MC} \right]$

 $\mathcal{L}_{\mathcal{E}} = \mathcal{L}_{rank} + \mathcal{D}_{KL}(q_{\theta}(w) \| p(w | \text{data}))$

 $\hat{\sigma}^2(y) \approx \frac{1}{T} \sum_{t=1}^T \mu_t^2 - (\frac{1}{T} \sum_{t=1}^T \mu_t)^2 + \frac{1}{T} \sum_{t=1}^T \sigma_t^2$

• Uncertainty

Robust Conditional GAN

Loss function

 $\mathcal{L}_{CGAN} = \mathbb{E}_{x, y \sim p(x, y)} \log(\mathcal{D}(x, y)) +$ $\mathbb{E}_{x \sim p(x), y' \sim p(y'), \tilde{y}' \sim \mathcal{T}(y')} \log(1 - \mathcal{D}(\mathcal{G}(x, y'), \tilde{y}'))$ $\mathcal{L}_{rec}^{y} = \mathbb{E}_{x \sim p(x), y' \sim p(y')} \frac{1}{2\hat{\sigma}'^{2}} \|\mathcal{E}(\mathcal{G}(x, y')) - y'\|_{2}^{2} + \frac{1}{2}\log\hat{\sigma}'^{2}$ $\mathcal{L}(\mathcal{G}, \mathcal{D}) = \mathcal{L}_{CGAN} + \lambda_{rec} \mathcal{L}_{rec}^{y} + \lambda_{cyc} \mathcal{L}_{cyc}$ $\mathcal{G}^* = \arg\min\max_{\mathcal{C}} \mathcal{L}(\mathcal{G}, \mathcal{D})$

