On the Fly Neural Style Smoothing for Risk-Averse Domain Generalization

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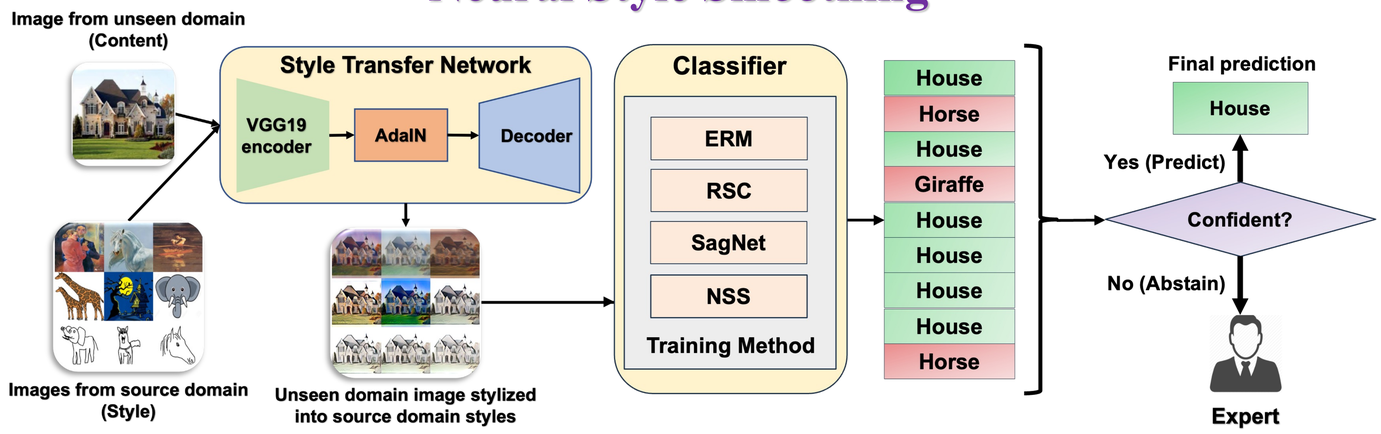
Motivation

- Machine learning (ML) models suffer a significant accuracy degradation on data from unseen domains.
- Recent works demonstrated the use of domain-specific information (e.g., image styles) for predictions as a potential cause for this accuracy degradation.
- This makes ML models unreliable for deployment in high-risk scenarios where misclassifications can have catastrophic consequences.

Contributions

- We propose an efficient inference procedure to obtain risk-averse predictions on the fly from a model by requiring only black-box access to it.
- We propose a training procedure relying on losses that enforce prediction consistency on random stylization of the training data.
- We demonstrate the effectiveness of our inference and training methods on benchmark datasets and their variations.

Neural Style Smoothing



- Let $\mathcal{X}$, $\mathcal{Y}$ be the data domain/labels, f be the classifier, and x_c/x_s be the content/style images, g/h be the encoder/decoder, then $h(t)$ is the AdaIn image with $t := AI(x_c, x_s) = \sigma(g(x_s))\left(\frac{g(x_c)-\mu(g(x_c))}{\sigma(g(x_c))}\right) + \mu(g(x_s))$.

- Given a classifier $f: \mathcal{R}^d \to \mathcal{Y}$, prediction of a style smoothed classifier $\psi: \mathcal{R}^d \to \mathcal{Y}$ on a sample x is given by

$$\boldsymbol{\psi(x) := \arg\max_{y \in \mathcal{Y}} P\left(f\left(h(t)\right) = y\right)},$$

where $t = AI(x, x_s)$, $x_s \sim P_S$ and P_S is the source distribution.

def $get\_counts(x, f, g, h)$:
  set cls_counts to zeros.
  for $i = 1, \ldots, n$ **do**
    Sample x_s^i from P_S
    $t = AI(x, x_s^i; g)$
    $x_{stylized} = h(t)$
    $pred = f(x_{stylized})$
    $cls\_counts[pred]$ += 1
  return cls_counts

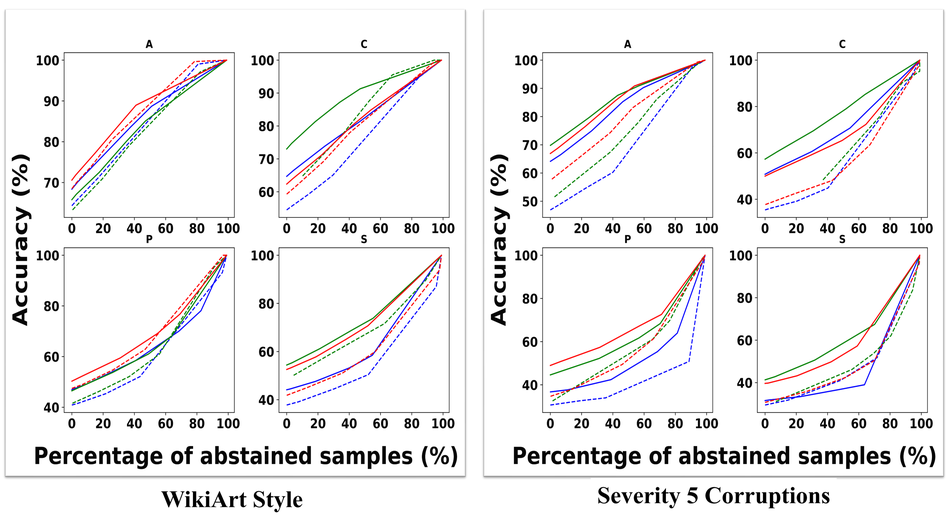
def $TT\_NSS(x, f, g, h, n, \alpha)$:
  $cls\_counts = \boldsymbol{get\_counts}(x, f, g, h)$
  $c_{max} = \arg\max_y cls\_counts$
  $n_{max} = cls\_counts[c_{max}]$
  if $\frac{n_{max}}{n} < \alpha$ ***then***
    return $ABSTAIN$
  else:
    return c_{max}

- NSS-based losses to improve risk-averse predictions.
  - **Style Augmentation**: $\mathbb{E}_{x_s \sim P_S}[\ell(f(h(t)), y)]$.
  - **Style Consistency**: $\mathbb{E}_{x_s \sim P_S}[KL(\bar{F}(x)) || F(h(t))] + H(\bar{F}(x), y)$, where $F: \mathcal{R}^d \to \Delta^{K-1}$ is the soft classifier of f and Δ^{K-1} is the probability simplex in $\mathcal{R}^K$, $H(\cdot)$ is the entropy and $\bar{F}(x) = \mathbb{E}_{x_s \sim P_S}[F(h(t))]$.

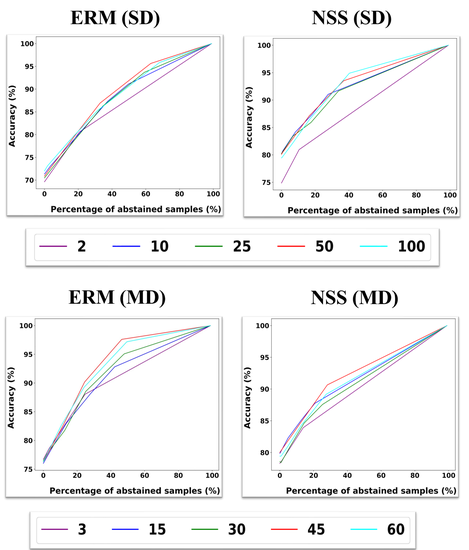
Test-Time Neural Style Smoothing (**TT-NSS**)

Key Results

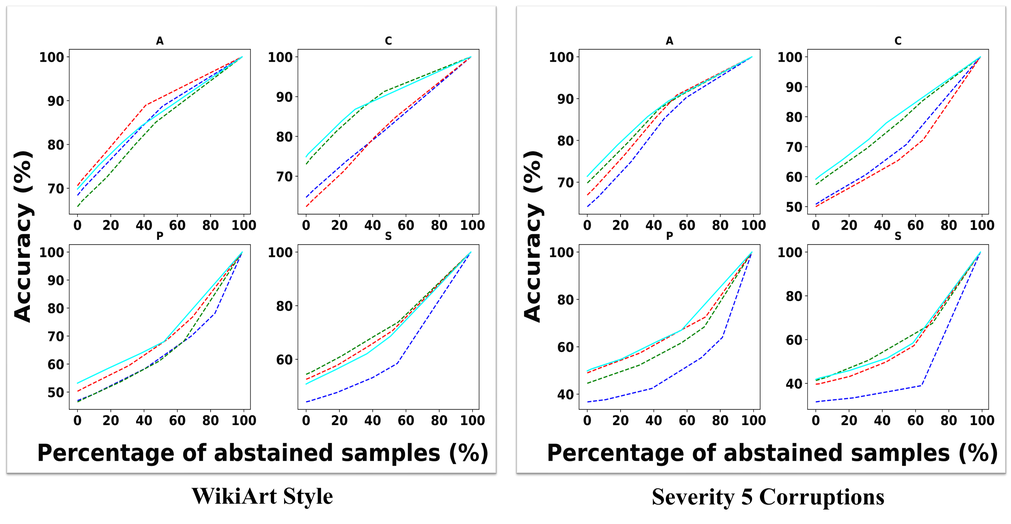
- TT-NSS produces better risk-averse predictions than the confidence-based abstaining mechanism.



- Effect of the number of re-stylizations, n, in TT-NSS.



- NSS trained models achieve better risk averse predictions than models trained with ERM.



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