Can Self-Supervised Representation Learning Methods Withstand Distribution Shifts and Corruptions?

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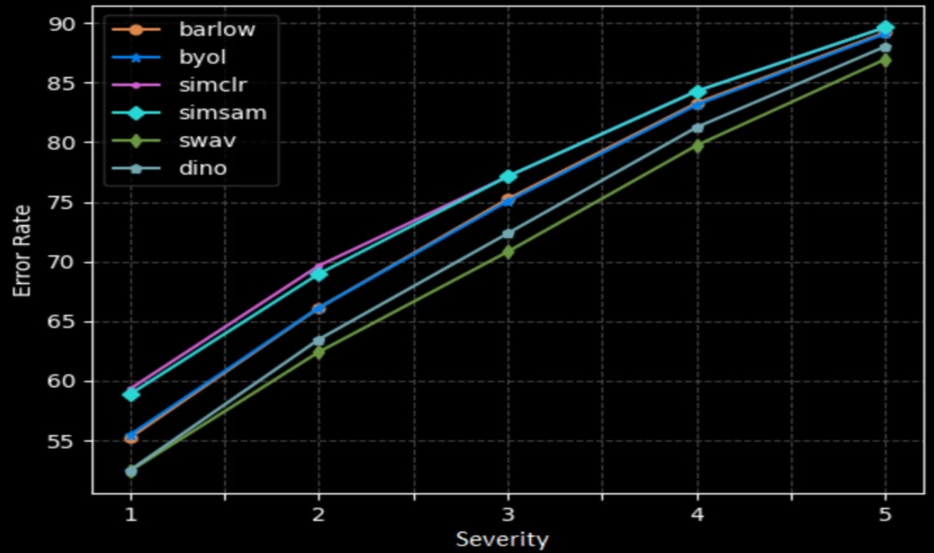
Motivation and Insights

- Research is needed to learn invariant SSL representations capable of handling distribution shifts and corruptions; this study provides a ground in this direction by sharing insights into the robustness performance of a large-scale dataset.
- We considered the most popular SSL paradigms, namely contrastive learning, knowledge distillation, mutual information maximization, and clustering. We exhaustively evaluated the corruptions, and their severity levels present in ImageNet-C dataset to understand the resilience of each method.



(Average over all corruptions)

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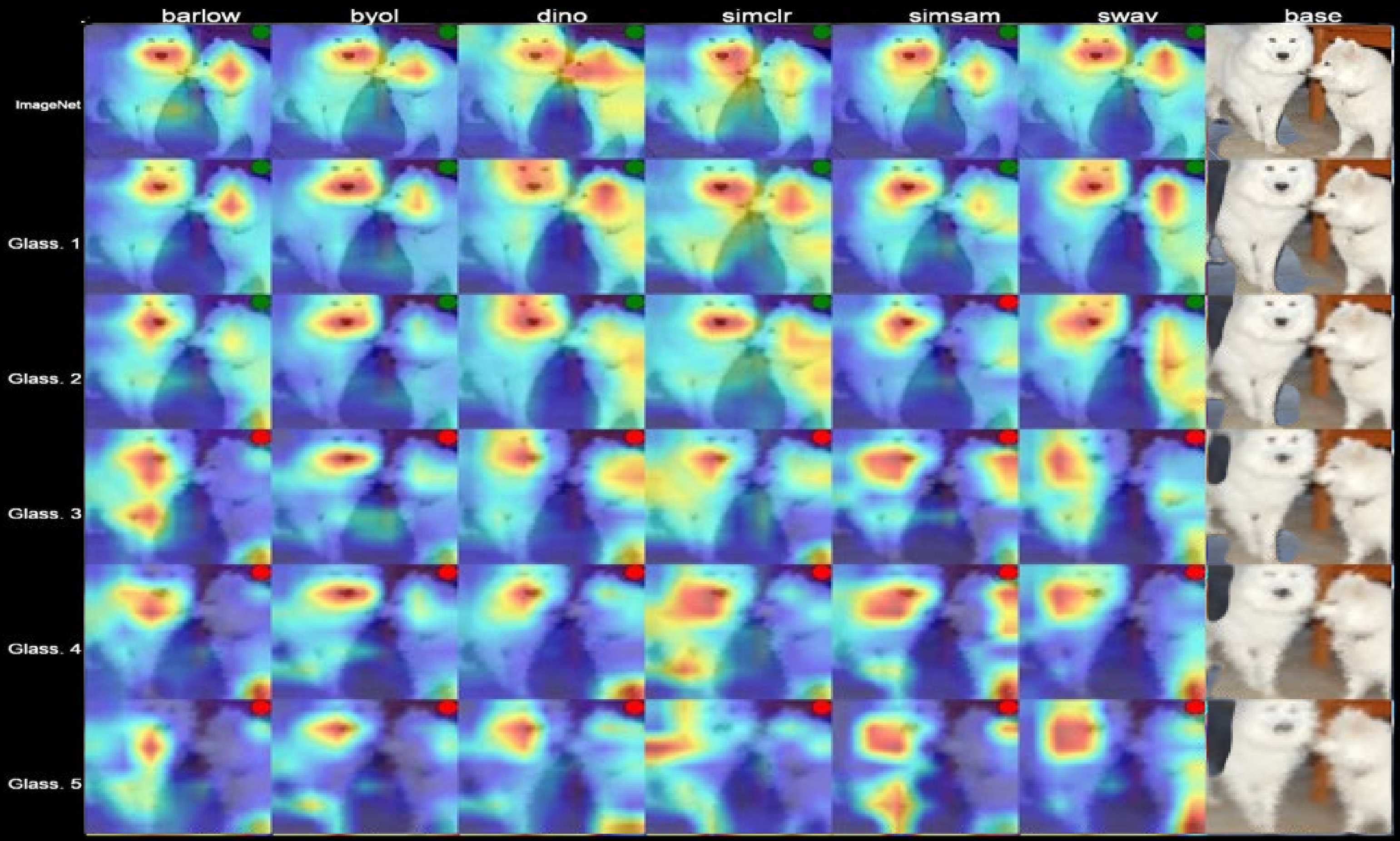
Why performance decreases? Visual Inspection



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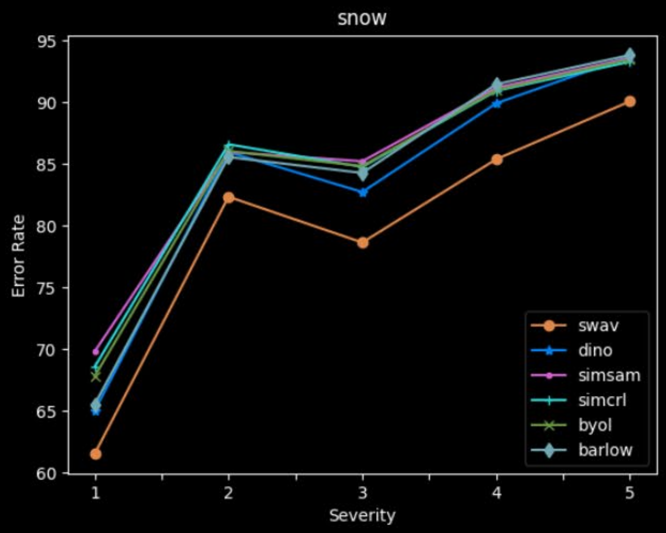
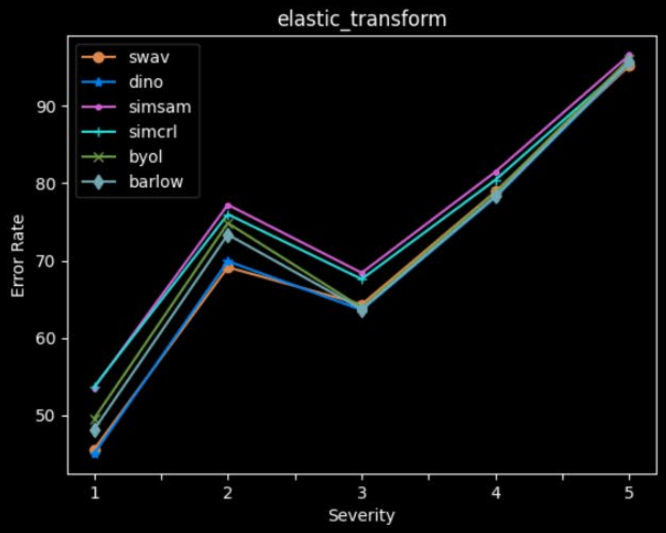
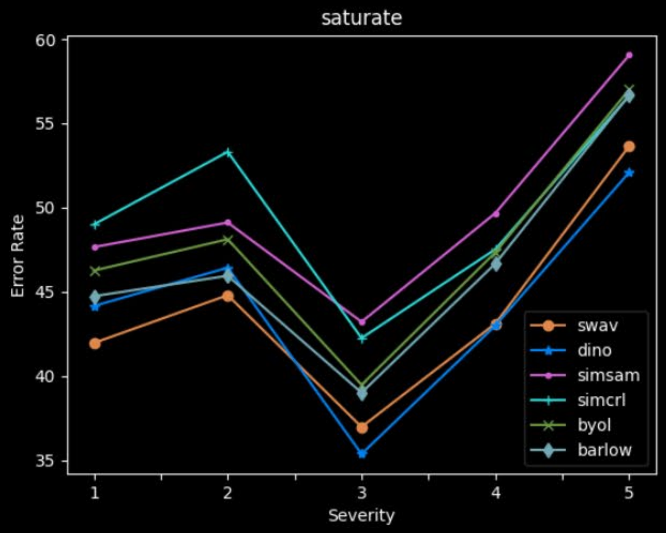
Does all corruptions behave uniformly across the severity level? No







Snow, elastic transform and saturate shows irregularities – explained the reason through similarity (SSIM)

Many questions to answer

Q1: How do self-supervised representation learning (SSL) paradigms perform in terms of robustness when exposed to distribution shifts and image corruptions?
Q2: To what extent can self-supervised representation learning methods maintain their robustness in the presence of distribution shifts, and what are the factors that limit their ability to do so?
Q3: What is the relationship between the robustness of different SSL paradigms and common categories of corruptions?
Q4: Do self-supervised representation learning methods deviate from the observed trend of error increase for certain corruptions, and what factors contribute to their robustness in the face of these corruptions?
Q5: To what extent does the presence of corruptions shift the focus of classifiers from overall representation to specific features?
Q6: Do different backbones, such as Convolutional Neural Networks (CNNs) and Transformers, influence the behavior and robustness?

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Thank you

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