

Scene Classification on Fine Arts with Style Transfer

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Agenda



- **01** Background
- **02** Methodology
- 03 Results
- **04** Conclusion



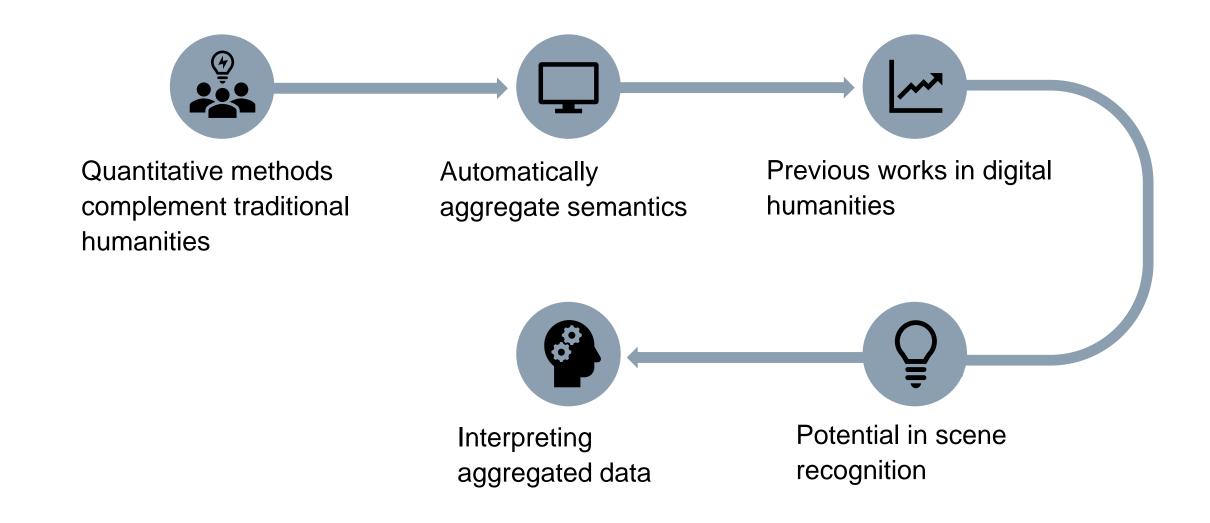
Sample images: Artistic stylized Places365 (left); Artwork: Landscape with river [7] (right)



Background

Background







Training and Evaluation Pipeline





Pretraining:

SWAG [1] and Hiera [2]

Task adaptation:

Places365-standard [3] for scene labels

Style transfer adaptation:

Artistic style transfer to provide artistic content

• Fine-Tuning:

Task-specific fine-tuning for scene classification

Evaluation:

Evaluation on unseen artworks

Task Adaptation

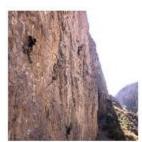


























Overview of the *Places365* [3] dataset. Places365-standard consists of 1.8 million images, 365 categories.

Places365-standard [3] for scene labels

ImageNet recognizes objects and classifies them to object labels (e.g. mountain tent)

Places 365 provides entry-level of an environment (e.g. mountain)

Q Challenges:

- Mismatch between historical and modern scenes
- Similar categories

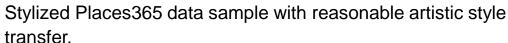
Applying Artistic Style Transfer



Artistic Style Transfer to provide artistic content

- ImageNet and Places365 are photographs
- Domain gap to artistic representation
- Adaptation via style transfer









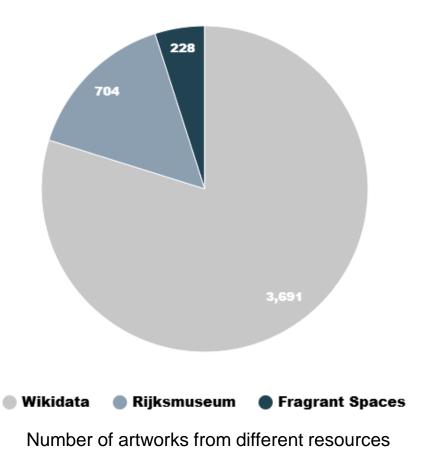
Stylized Places365 data sample with unnatural style transfer





Artworks Source Distribution

- Artworks from Wikidata [5]
- Artworks from Rijksmuseum [6]
- Fragrant Spaces from ODOR [8] dataset



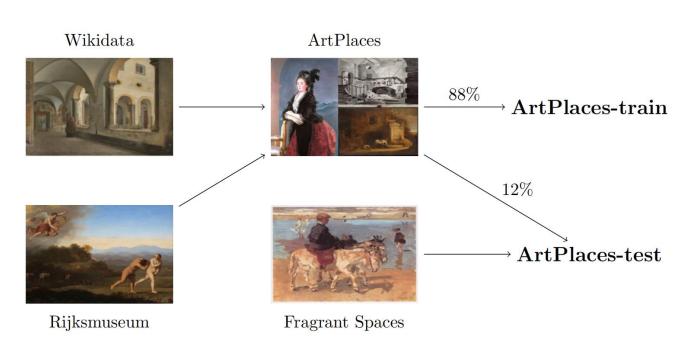
[5] https://wikidata.org

[6] https://rijskmuseum.nl

[8] Zinnen M: Smelly, dense, and spreaded: The Object Detection for Olfactory References (ODOR) dataset

Fine-tuning with Artworks: data reallocation





Separation of artworks to form training and test sets.

Dataset Assembly

- Combine Wikidata and Rijksmuseum
- ArtPlaces split into two sets
- ArtPlaces-train for fine-tuning
- Rest of Artplaces: labels are manually corrected
- ArtPlaces-test: corrected artworks and Fragrant Spaces for evaluation

Challenge:

Non-scenery artworks



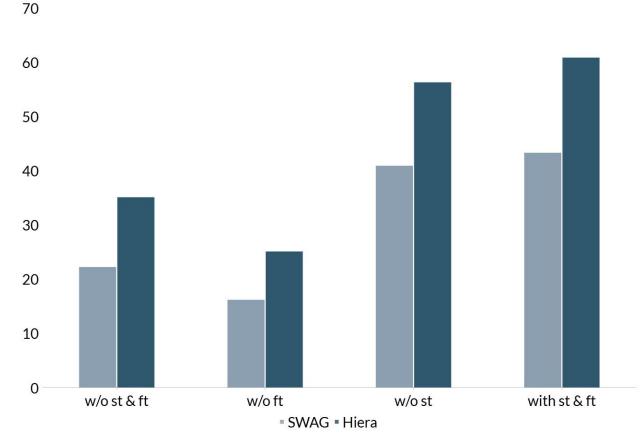
Results

Results

Quantitative Analysis



Scene Classification Prediction: Topk@5 Accuracies



Prediction results: the suffix "st" refers to stylization, and the suffix "ft" is the abbreviation for fine-tuning.

Evaluation on Artworks

- Hiera-ViT/B surpasses SWAG-ViT/B in all the conditions.
- The fine-tuning dominates the contribution in increasing performance.
- Combining stylization and fine-tuning leads to best results.

Results

Qualitative Analysis



Predictions over different settings with the following exemplar images





Example images for evaluating the networks. *Glacier in Magdalena Bay, Spitsbergen* Friedrich Kallmorgen (left); *The Water Lily Pond* by Claude Monet (right)



Conclusion

Conclusion



Benchmark in artistic scene recognition

Applying a multi-stage domain adaptation training strategy.

Challenges

Intra-class variation and semantic ambiguity across categories

Scene categories

Historical artwork specific categories

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Combined training

Combination of stylization and fine-tuning

Data cleaning

Non-scenery paintings with unclear scene categories

Varying styles of artworks

Asserting a prior style classification network

References and Image Credits



- [1] Singh M, Gustafson L, Adcock A, et al. Revisiting weakly supervised pre-training of visual perception models
- [2] Ryali C, Hu Y T, Bolya D, et al. Hiera: A hierarchical vision transformer without the bells-and-whistles
- [3] Zhou B, Lapedriza A, Khosla A, et al. Places: A 10 million image database for scene recognition
- [4] King Candaules by Jean-Léon Gérôme © Museo de Arte de Ponce; Rivierlandschap met koeien by Aelbert Cuyp © Rijksmuseum (Accession No. SK-A-3957); Portrait of Cornelis Pietersz. Hooft by Cornelis van der Voort © Amsterdam Museum (Accession No. SB5824)
- [5] Landscape with river by Jan Griffier © National Gallery of Armenia (Accession No. 749)



Thank you for your listening!