# Style Transfer Dataset And Insights for Future Stylization Improvements

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## Goal of research

Find objective features of a stylized image that affect subjective human perception of the image.

## One-slide talk

#### Motivation

Explore drawbacks of current stylization models for future studies

- Manual data markup
- Make assumptions about the influence of various factors on the quality of stylization
- Figure out how to test these assumptions and verify them



#### Goal

Find dependencies between scores and some characteristics of stylizations and evaluate their influence on the final quality of the stylization

#### Problem statement

The concept of stylization does not have a clear constructive definition. There are several formulations of the stylization problem, each of which produces different results.

Therefore, it is proposed to create a marked dataset with subjective evaluations of stylizations created by the modern model and to analyze the image characteristics that influence human perception of stylization.

Each of them relies on some heuristic observation made on the basis of subjective human understanding of stylization

## Hypothesis and quality criterions

Since each person's perception is subjective, we do not aim to obtain a dataset with highly correlated scores. We assume that there are image properties that are on average well correlated with human preferences, i.e., that do not depend on the preferences of a particular person.

Therefore, if we can identify some invariant properties, this will be the result of our work

#### Solution

Therefore, it is proposed to create a marked dataset with subjective evaluations of stylizations created by the modern model and to analyze the image characteristics that influence human perception of stylization.

Our work is divided into 2 phases:

- ► Dataset partitioning
- Analysis of stylization quality scores

## Dataset description

```
\begin{split} \textit{Dataset} &= \{\textit{I}_{(\textit{style},\textit{content},\textit{size})} \mid \\ (\textit{style},\textit{content},\textit{size}) &\in \textit{Contents} \times \textit{Styles} \times \textit{Sizes}) \} \\ |\textit{Contents}| &= 50, \; |\textit{Styles}| = 50, \\ \textit{Sizes} &= \{150, 300, 500, 700\}, \; \textit{labels} = \overline{1,10} \end{split}
```

## Scores consistency

	A1	A2	A3
A1	1.0	0.39459	0.346416
A2	0.394590	1.0	0.412650
А3	0.346416	0.41265	1.0

Table: Kendall tau-c rank correlation coefficient between scores of different annotators

	A1	A2	A3
A1	1.0	0.517117	0.461340
A2	0.517117	1.0	0.541933
А3	0.461340	0.541933	1.0

Table: Spearman rank correlation coefficient between scores of different annotators

#### Scores distribution

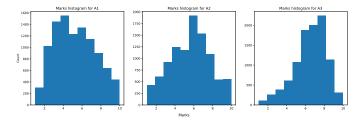


Figure: Scores distributions for different annotators

## Key observations

After marking up, we came up with a few hypotheses.

- Images with low contrast are rated lower
- Images with low diversity of colours are rated lower
- Images with high sharpness background are rated lower
- Loss of contours in stylisation leads to a lower score
- ► The appearance of borders on smooth surfaces after stylization reduces scores
- ► The more faces on content image are altered by stylization, the lower the score
- ► There is stronger negative correlation between scores and sky smoothness than the average between scores and background
- Contrast between color characteristics of close and background objects increases score

## Correlation tests for Color features (theory)

#### For colors we use CIELAB format:

$$I_{(content, style, size)} \in \mathbb{R}^{N \times M \times 3}, \ L = (I_{ij1})_{i=1, j=1}^{N, M}$$
 (1)

$$a = (I_{ij2})_{i=1,j=1}^{N,M}, b = (I_{ij3})_{i=1,j=1}^{N,M},$$
(2)

$$L_{mean} = \mu_I, \tag{3}$$

$$C_{RMS} = s_L, (5)$$

$$C_{webber} = \frac{\max(L)}{\max(\min(L), 1)} - 1, \tag{6}$$

$$CD_{ab\_rms} = \sqrt{s_a^2 + s_b^2} \tag{7}$$

(8)

## Correlation tests for Color features (results)

	Kendall tau-c			Spearman		
	A1	A2	A3	A1	A2	А3
L <sub>mean</sub>	-0.015	-0.061	-0.049	-0.022	-0.090	-0.073
C <sub>RMS</sub>	0.237	0.184	0.167	0.349	0.273	0.245
C <sub>webber</sub>	0.074	0.031	-0.000	0.107	0.043	-0.001
CD <sub>ab_rms</sub>	0.103	0.081	0.111	0.154	0.120	0.166

Table: Kendal tau-c and Spearman correlation for color metrics

## Correlation tests for Face embeddings distance

The cosine distance between face embeddings on the content and on the stylised image was used to assess face similarity. Embeddings were obtained by applying the VGG-face model from the DeepFace library.

$$Sim = Cosine(emb_{content}, emb_{stylization})$$

	Kendall tau-c				Spearman		
	A1	A2	A3	A1	A2	А3	
Sim	-0.373	-0.399	-0.45	-0.53	-0.565	-0.624	

Table: Kendal tau-c and Spearman correlation between Sim and scores

#### Conclusion

## Style Transfer Dataset And Insights for Future Stylization Improvements

We proved that the subjective perception of stylisation depends on the following factors:

- ► Images with low contrast are rated lower
- ▶ Images with low diversity of colours are rated lower
- ► The more faces on content image are altered by stylization, the lower the score