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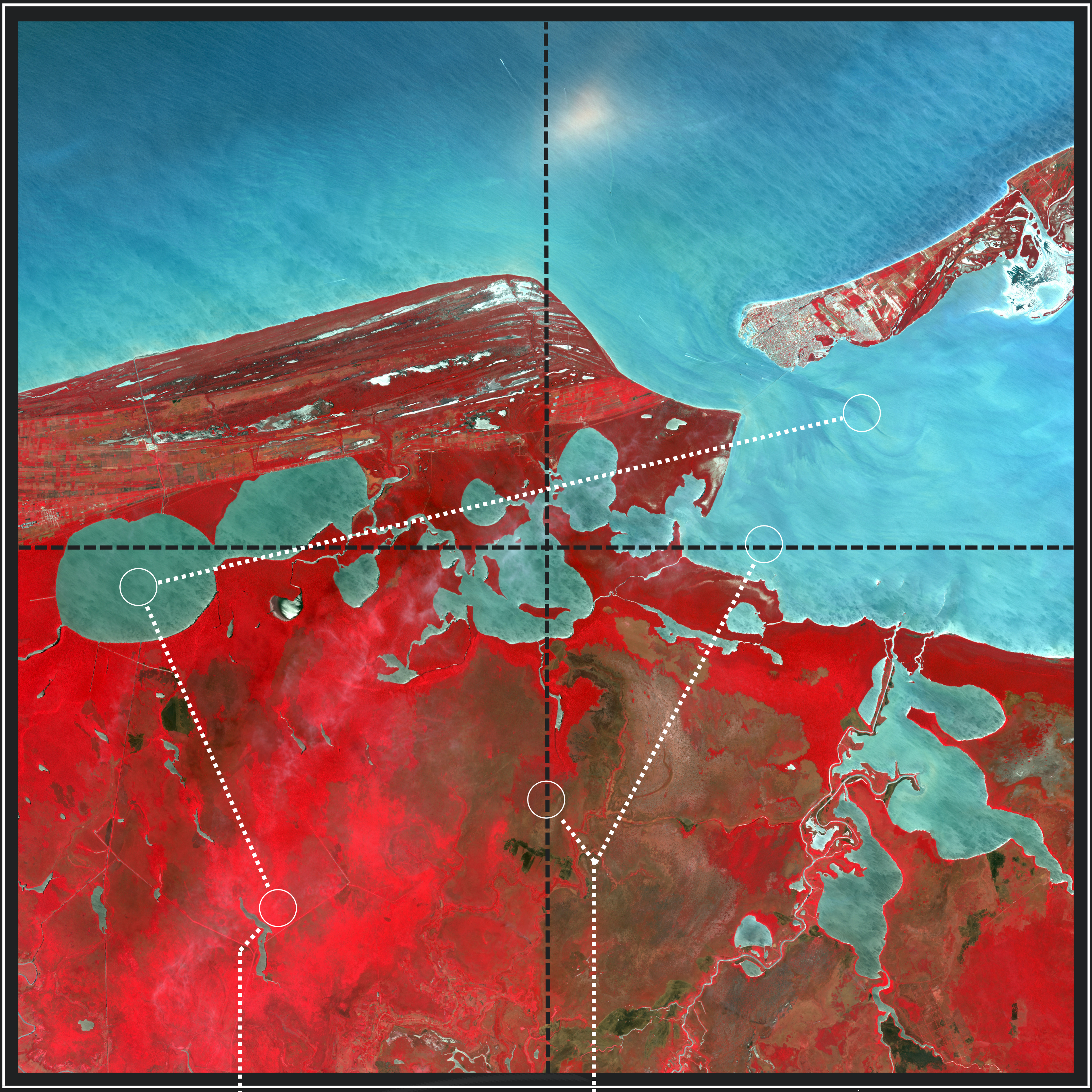
Beauty in the Eye of the Machine:

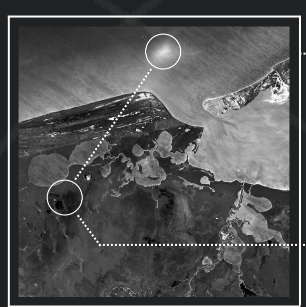
How automated measures of aesthetic beauty can improve GAN output



Saturation
The strength of colour in regard to a single channel, complete desaturation is grey.

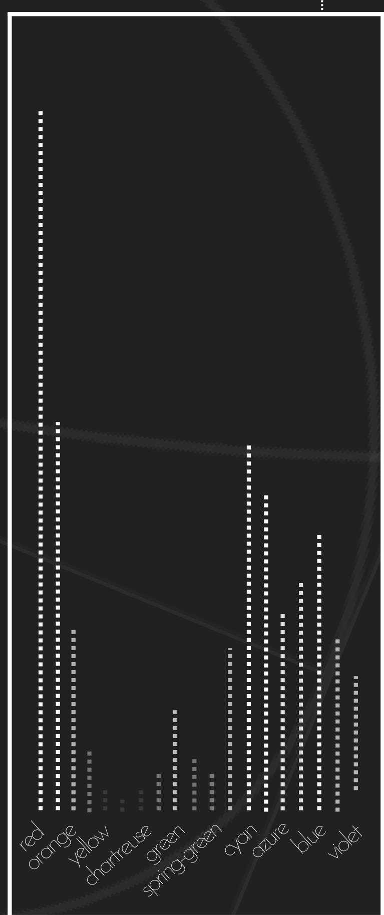
Symmetry
The 'mirrored' the image is around some axis

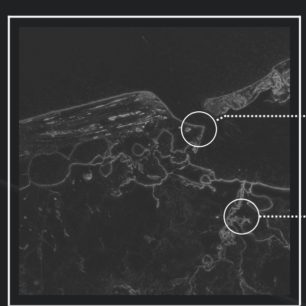
Histogram
A graph depicting the distribution of hues in an image



Luminance
Perceived 'brightness', measured by averaging the greyscale values.

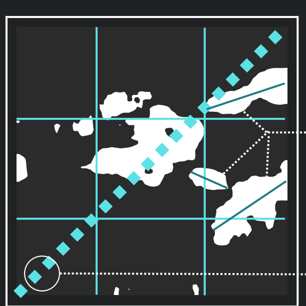
Contrast
The difference between the highest and lowest values in a greyscale image.





Sharpness
Having defined and distinct edges. A measure of blurriness

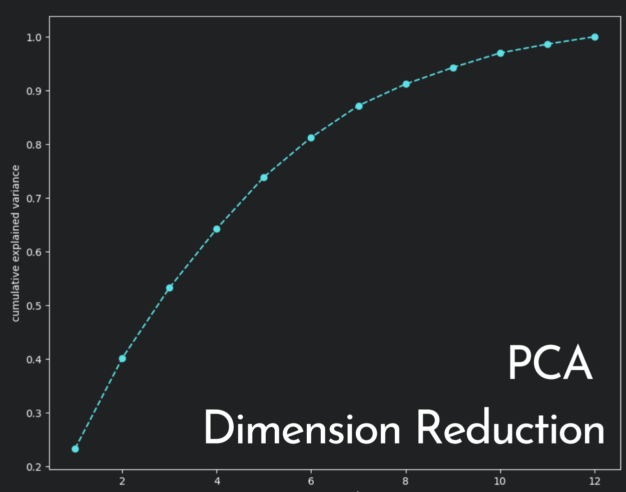
Entropy
Number of bits to encode an image, describing the image's complexity.



Line Ratios
The ratio of horizontal to vertical lines, as well as horizontal and vertical to diagonal

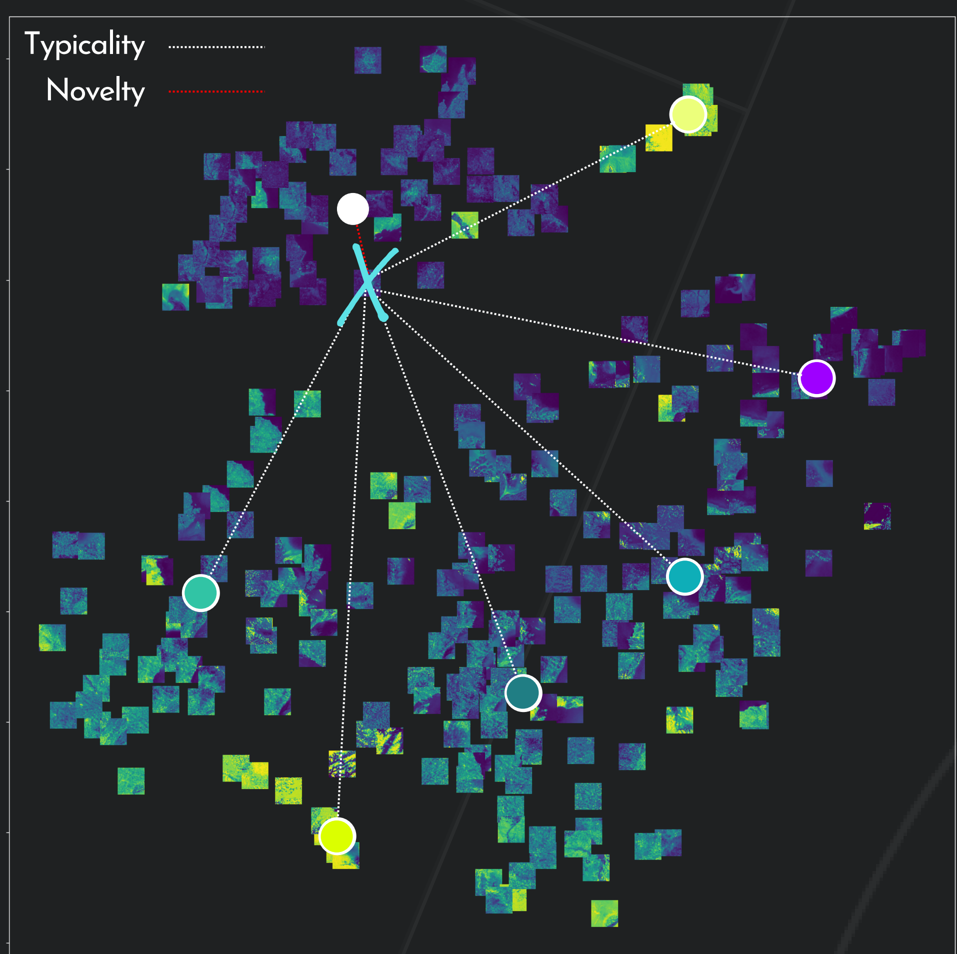
Rule of Thirds
Compositional practice, placing points/objects of interest along gridlines or at their intersection. Grid divides image into thirds.

Diagonal Dominance
Compositional practice of placing objects of interest along image diagonals.



PCA
Dimension Reduction

K-Means
Clustering
K Values



1. Background

Computational aesthetics: automated methods of measuring how beautiful something is.

Until now most of the metrics used are either superficially visual or basic morphological/spatial, e.g. colour measures [1][6], composition [2][5], morphological component shape and orientation [3][6], entropy and compression complexity [4][6], luminance [1][6], among many more.

Humans consider things in a context, through the lens of their own subjective experience, not simply in isolation and only considering the visually apparent aspects with no relation to other parts of their life. This is why I propose building a contextual model for images and grading it through the metric of typicality and novelty [7].

Typicality and Novelty: Stimuli that are typical allow for faster, easier, and smoother perception, reducing the effort and duress on the observer. Novelty allows for learning and cognitive stimulation. [7] From this we can suppose a balance between the two will provide a positive experience for the observer.

2. Questions

- How can automated measures of aesthetic beauty of an image improve GAN output?
  - What measures of aesthetics are the best predictors for human ratings of aesthetic beauty?
  - Does including the contextual approach of typicality and novelty improve the correlation between automated aes-thetic rating and human aesthetic rating?

3. Methodology & Experiment

- Find potentially predictive visual and spatial features
- Create software pipeline to extract features
- Process and aggregate features

- Using feature data, perform Principal Component Analysis
- Using dimensionally reduced feature space, perform K-Means Clustering
- Using clusters, generate Typicality and Novelty

- Have people vote on which images in the dataset are "most pleasing to the eye"
- Perform Ordinary Least Squares Regression on feature data with aesthetic votes including and excluding Typicality and Novelty
- Compare the fits of the two models
- Analyse individual statistical significance of each feature

4. Results

OLS I: Adjusted R-Squared = 0.396
OLS II: Adjusted R-Squared = 0.421
Increase of +6.31%

5. Conclusions

- The most consistently significant features are saturation, histograms, contrast, and horizontal to vertical line ratio.
- Novelty is a significant feature, Typicality is not.
- There is a slight increase in model fit (predictability) when including typicality and novelty, however it both fits are still moderate at best.
- There may be interference since the contextual features were made using the visual and spatial features. Further investigations into how to encode typicality and novelty can produce more independent features and offer a better improvement.

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*Rule of Thirds
**Horizontal to Vertical Line Ratio
***Straight to Diagonal Line Ratio

[8] United States Geological Survey, 2020.