Utilizing Convolutional Neural Networks to Predict Style of Paintings.

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General Assembly DSI Project 5 | 03/24/23

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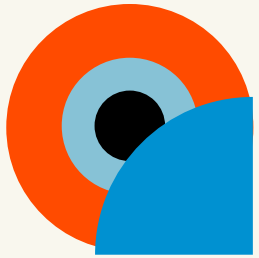


Introduction & Background

Why might someone need this ML model? (The backstory) Vocabulary

Data Collection & Cleaning

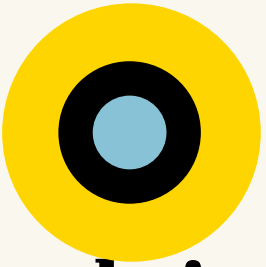
The origins of our dataset and our process for preparing it.

EDA & Visualization

Interesting snippets and statistics about our dataset.

Modeling Process

The different models we evaluated (& how they differed).



Conclusion & Next Steps

Results, explanations, steps forward, and the epilogue to our story.

BONUS: Audience interaction!

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Can a painting's art style be predicted by using the image in a CNN model?

Photo by Allef Vinicius on Unsplash

- Neural networks as a "magic bullet".
- So. Many. Art styles.
- Can be hard to distinguish between, even for art ~~experts~~ aficionados.
- CNN for predicting art style from image pixel data.

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Story Introduction / Problem Statement

- **Art thieves** who pulled off the heist of the century.
- Team's resident art expert was KIA.
- No idea how to fence the stolen art without **knowing the art styles**.
- Getting a **new art expert** is too risky.
- **Train a CNN machine learning model** instead!

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Neural Net Vocabulary.

- Convolutional Neural Network (CNN)
- RGB Pixel Arrays
- Convolution Filters
- Kernel Size
- Batch Normalization
- Regularization
- Dropout Layer
- Dense Layer

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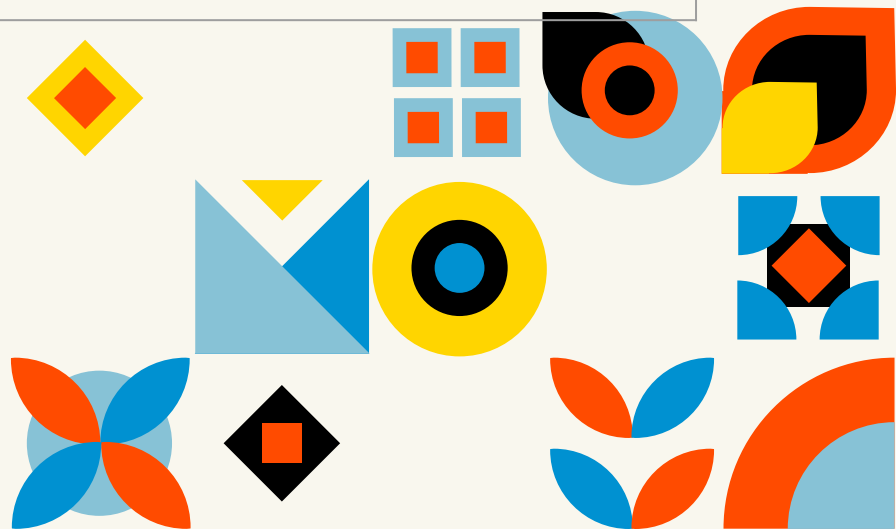
Data Dictionary.

Style -artwork style	**Link** - url for image	**V_Sent** - sentiment analysis
Artwork - art name	**Language** - origin language	**Hex** - color code
Artist	**Translated** - translated art name	**Color** - main color of work
Date	**Style Num** - number for style	

Data Description:

- Data Source : Kaggle
- Data Size : ~120k x 5 columns elements before cleaning
- Data Shape : 89,545 rows x 11 columns after cleaning
-



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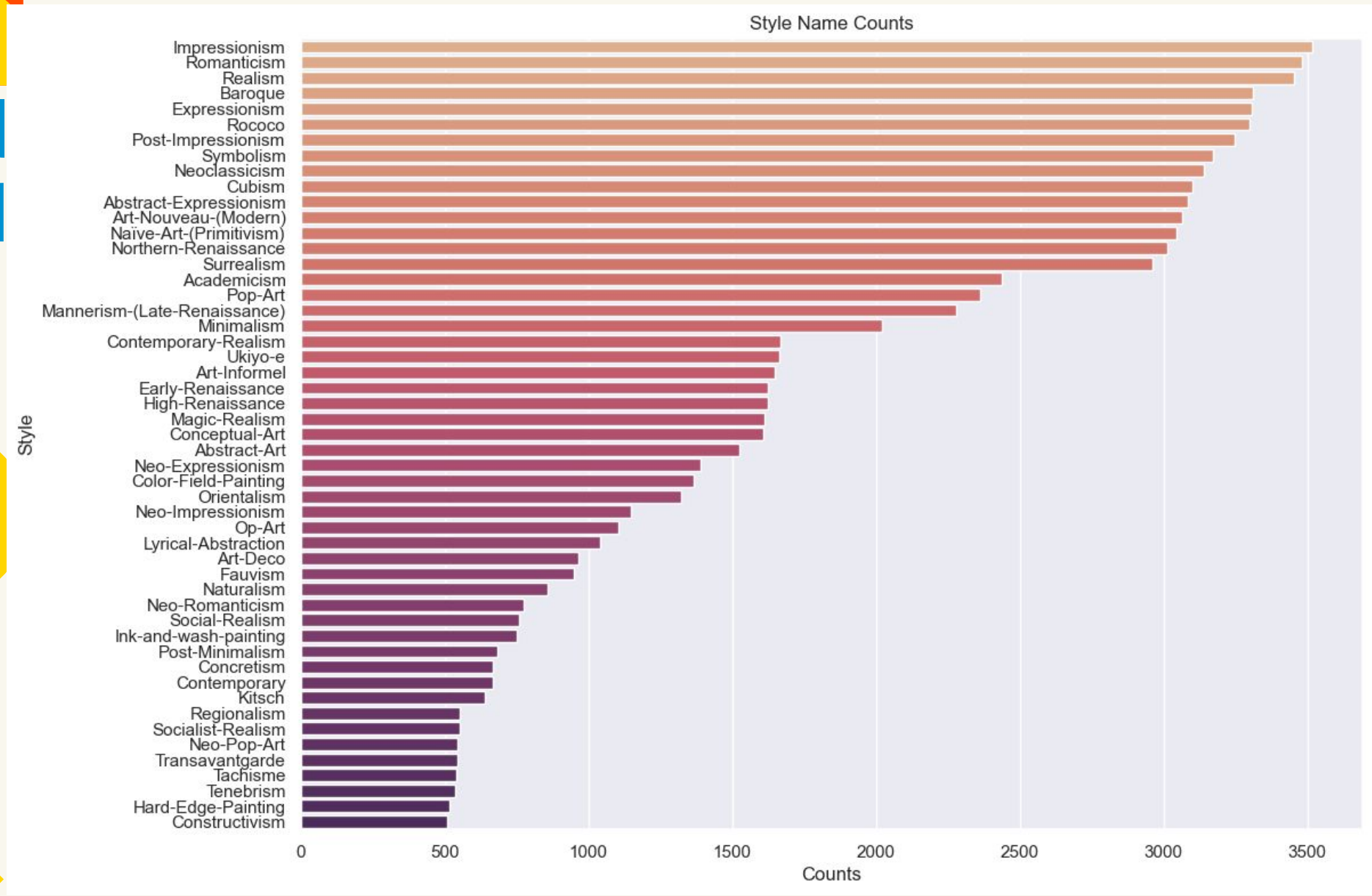

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Data Cleaning

- Drop bad URL's
- Drop duplicate artwork
  - Sketches for final work
- Drop styles with less than 500 pieces
- Date column
  - Remove hyphens from date ranges
    - Keep first date
  - Change century dates to numeric
    - VII → 600 (ad)
    - Drop BC dates

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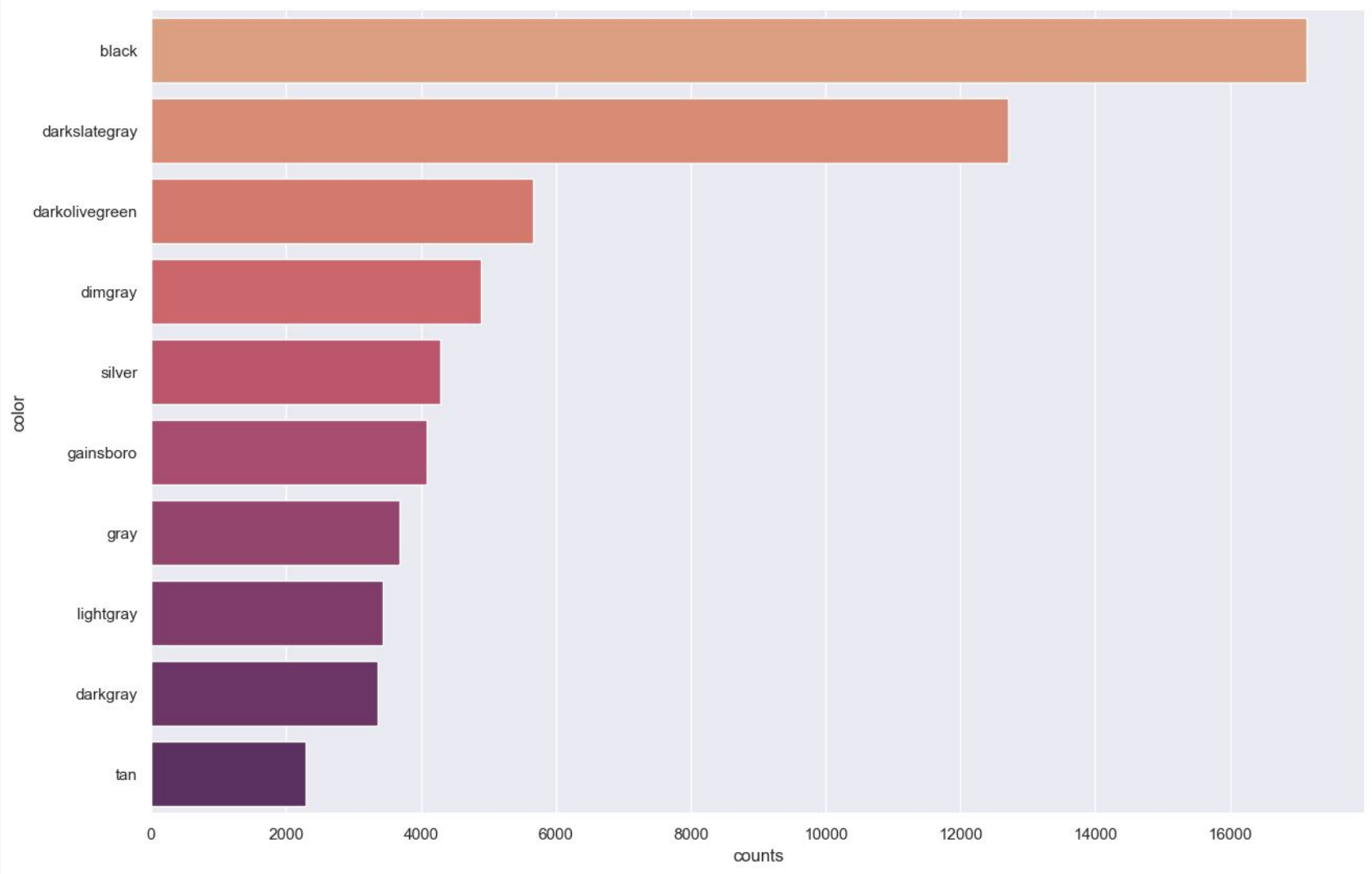
Feature Engineering

- Translated
- V_sent
- Style Number
- Color
- Language
- Hex



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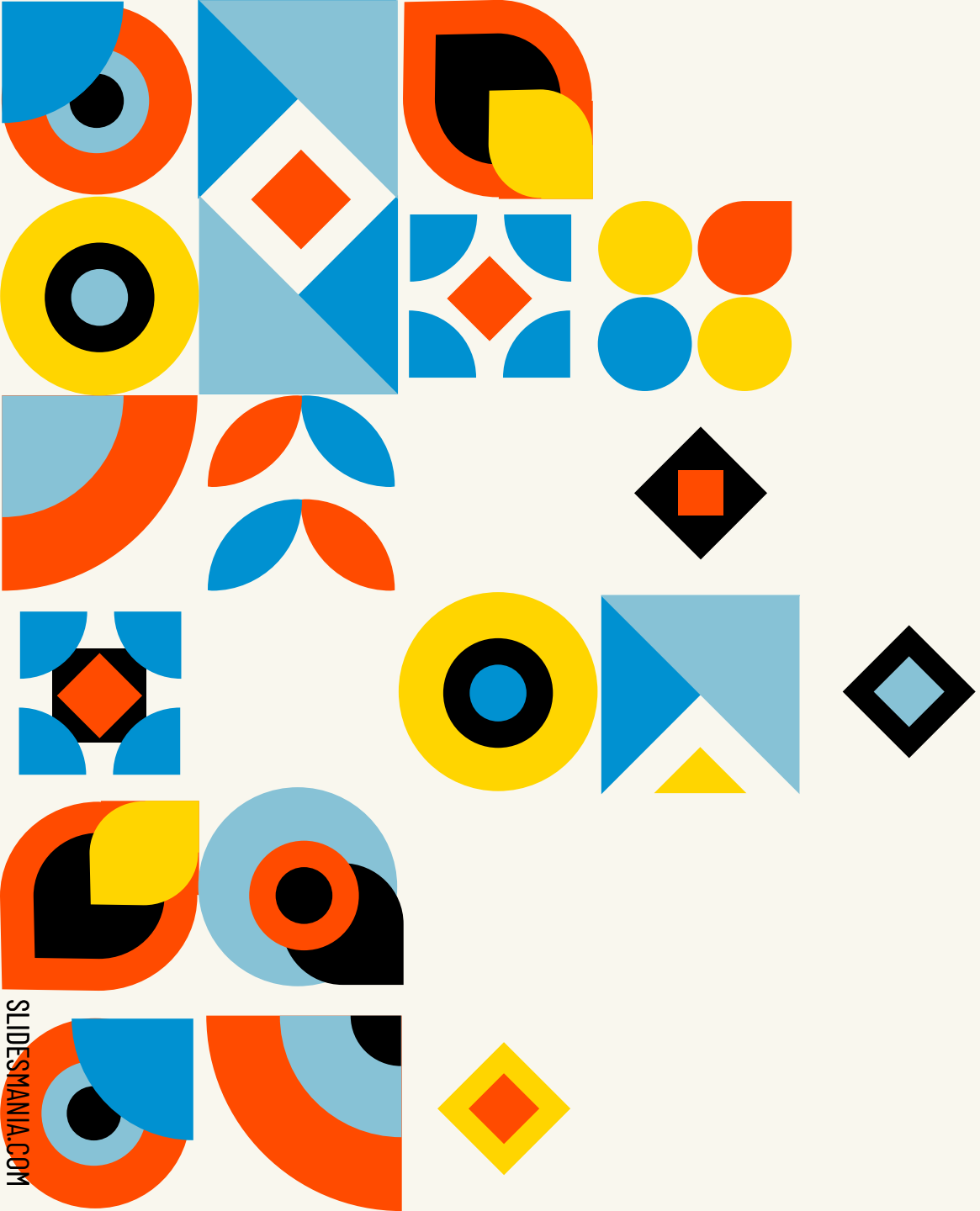

EDA!

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Scatter of Style by Date
v_sent_trans
0.5
0.0
−0.5
Style
Abstract-Art
Abstract-Expressionism
Academicism
Art-Deco
Art-Informel
Art-Nouveau-(Modern)
Baroque
Color-Field-Painting
Conceptual-Art
Concretism
Constructivism
Contemporary
Contemporary-Realism
Cubism
Early-Renaissance
Expressionism
Fauvism
Hard-Edge-Painting
High-Renaissance
Impressionism
Ink-and-wash-painting
Kitsch
Lyrical-Abstraction
Magic-Realism
Mannerism-(Late-Renaissance)
Minimalism
Naturalism
Naïve-Art-(Primitivism)
Neo-Expressionism
Neo-Impressionism
Neo-Pop-Art
Neo-Romanticism
Neoclassicism
Northern-Renaissance
Op-Art
Orientalism
Pop-Art
Post-Impressionism
Post-Minimalism
Realism
Regionalism
Rococo
Romanticism
Social-Realism
Socialist-Realism
Surrealism
Symbolism
Tachisme
Tenebrism
Transavantgarde
Ukiyo-e
700
780
860
940
1,020
1,100
1,180
1,260
1,340
1,420
1,500
1,580
1,660
1,740
1,820
1,900
1,980
2,060
Date

Tableau Dashboard

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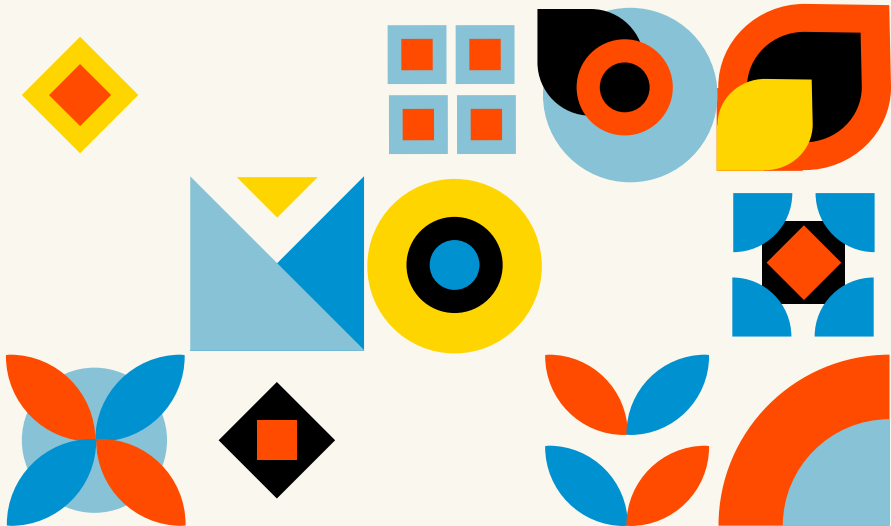
Photo by Steve Johnson on Unsplash

Preprocessing

Problems in preparing data for modeling

- Converting imgs into arrays
- Filepaths to imgs
- Creating DF of matrices

The solution?



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Preprocessing Solution

Tensorflow Keras (*image_dataset_from_directory* function)

- Faster, easier, higher quality
- BatchDataset
- 250x250 pixels
- Categorical Labels

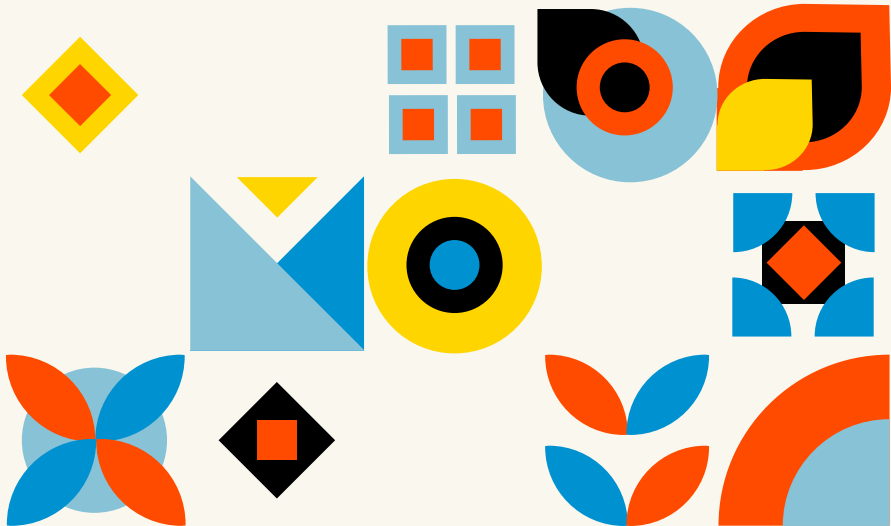

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Photo by Steve Johnson on Unsplash

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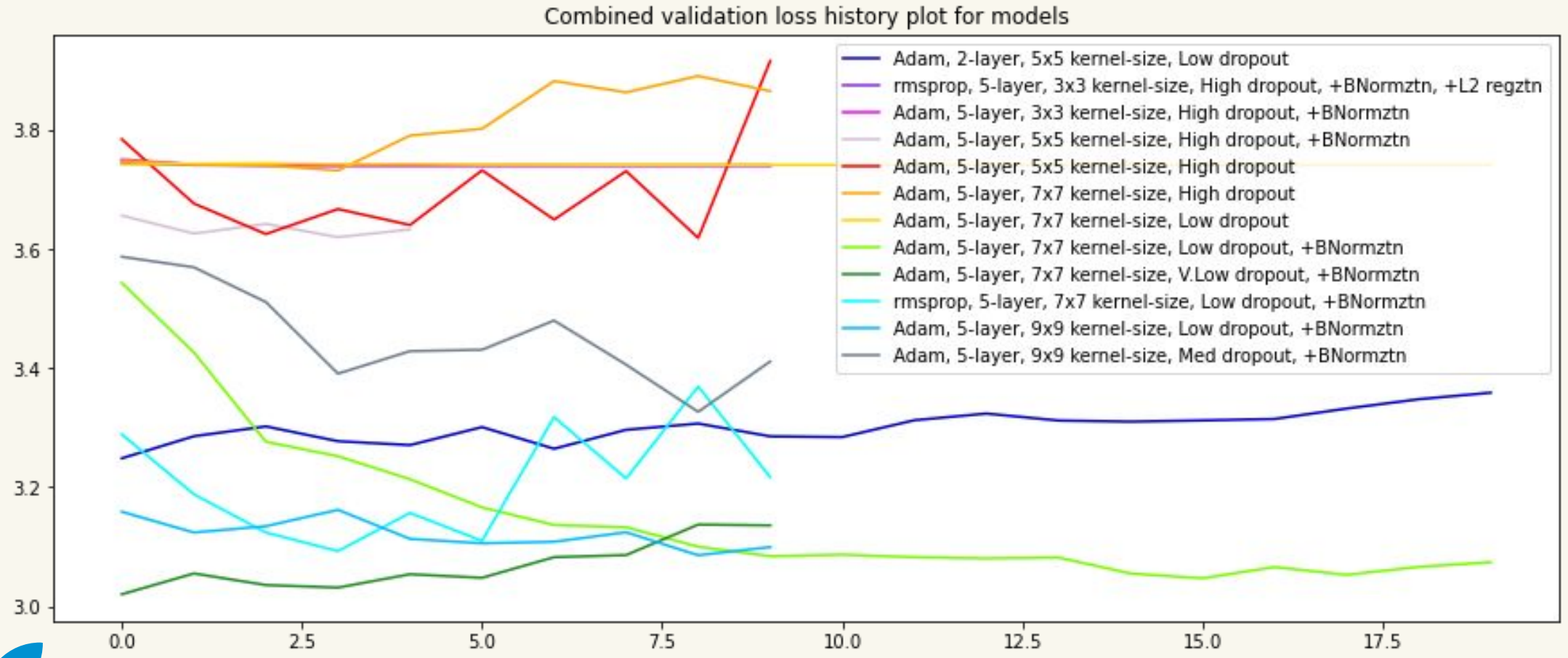
Sometimes, things don't always go to plan



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Model Summaries.

baseline: .0397

Model	Train Loss	Validation Loss	Train Acc	Validation Acc
CNN with rmsprop	3.2450	3.2479	0.1456	0.1326
CNN with 3 Dense Layers	2.8841	3.079	0.1989	0.1672
CNN with 9x9 Kernel Size and Dropout (.1 - .2)	3.0910	3.0995	0.1628	0.1599
CNN with BatchNormalization and Dropout (.5-.1)	2.6489	3.159	0.2560	0.1797
CNN with 5 Filters, 7x7 Kernel Size, Dropout(.1 - .2), & BatchNormalization	3.0741	3.0341	0.1742	0.1783

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Recommendations

- Have some prior knowledge on what you're about to steal, helps a lot
- Don't steal 100,000 artworks at one time, or at least make sure they're all the same style
- Making a machine learning model can takes more time than the cops are giving us
- The model can't direct us much, so lets hope museums have a buy-back program

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Next Steps.

- More Time, More Processing Power
- Combine Classes or Reduce Them
- Less downsizing, Experiment with more Models

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Expressionism or Romanticism?

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Conclusion: Failed Model but Successful Experience

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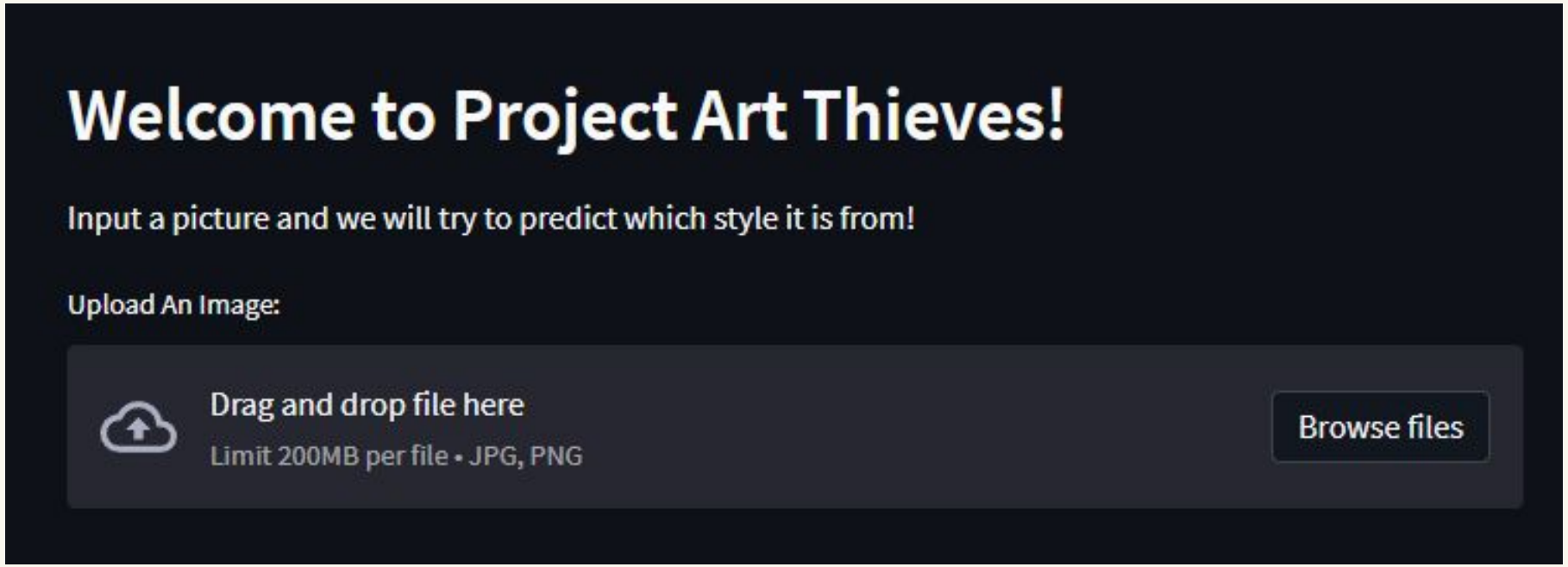
Streamlit Application!



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Questions ?

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