# DART: Deep learning for ART

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## Art Forgery Detection

**Art Forgery**

- Famous painters fetch $$$ in art world (museums, private collectors).
- This incentivizes forgeries.
  - Ex- Han van Meegeren sold $30 million worth forgeries in 1967.

**Forgery Detection**

1. Analog techniques- Carbon dating (age), X-ray diffraction (pigment analysis) etc.
2. Digital techniques-
   a. Wavelet decomposition (brush stroke analysis)
   b. Deep learning (painter specific image features)

## Featurizing Art

**Convolutional Neural Networks**

- Convolutional neural networks can be used for ‘guided’ featurization of images.
- Given (image, label) pairs, it can decompose the image into features such that different labels have different features.
- This can be used to find labels of new images (supervised learning).

**Painting Classification**

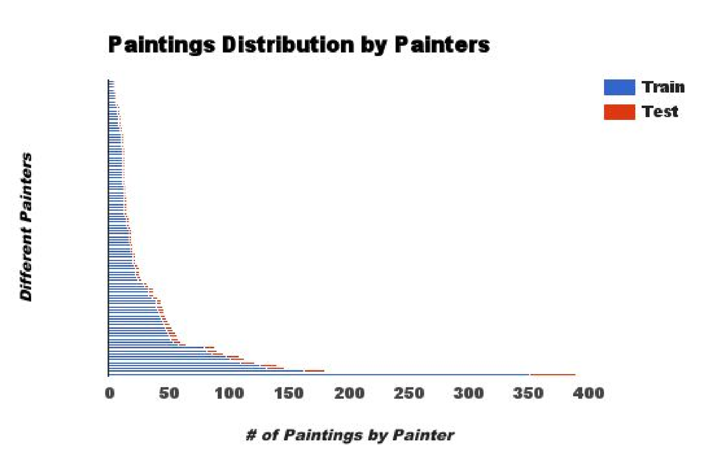
- Given a painting and a label (genre, painter, era), identify features that distinguish paintings with different labels.
- Previously applied to genre prediction and painter prediction (~100 paintings).

## Dataset

**Original**: 80,000 paintings from Kaggle (originally from wikiart.org) with paintings, genres and era labels.

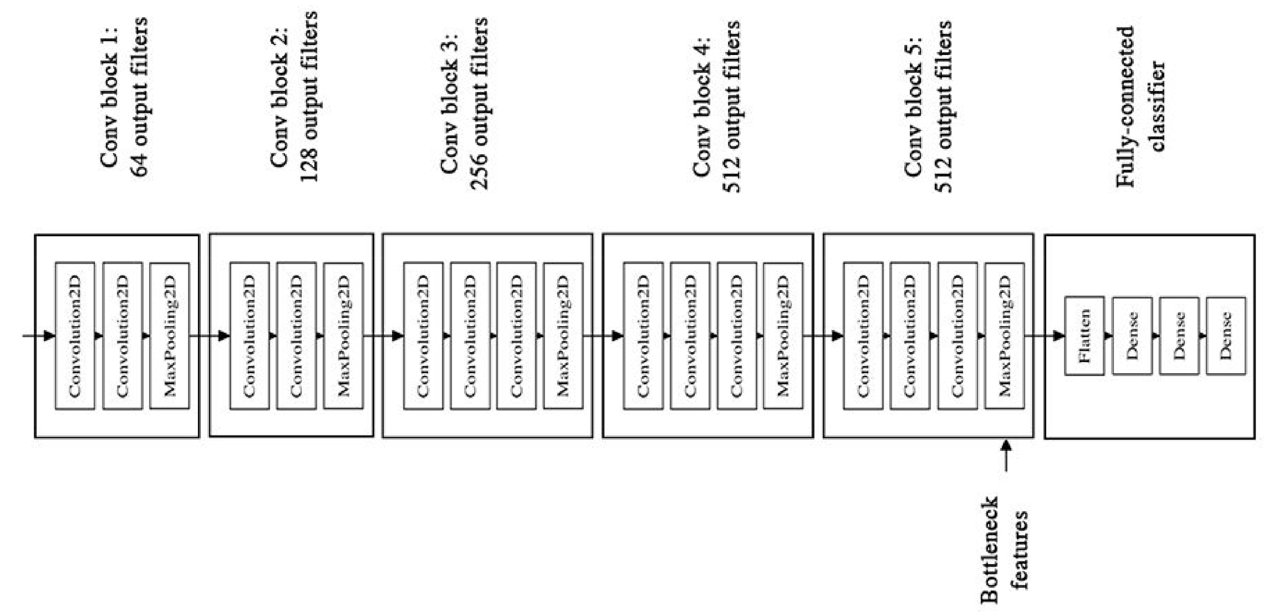
**Subset**: We select 100 random painters from 1584 total painters in the dataset. This correspond to 3529 paintings.

**Train-test split**: We use a stratified split across the 3529 paintings to obtain a train set of 3171 paintings and a test set of 358 paintings.




## Methods

1. **CNN + NN**:

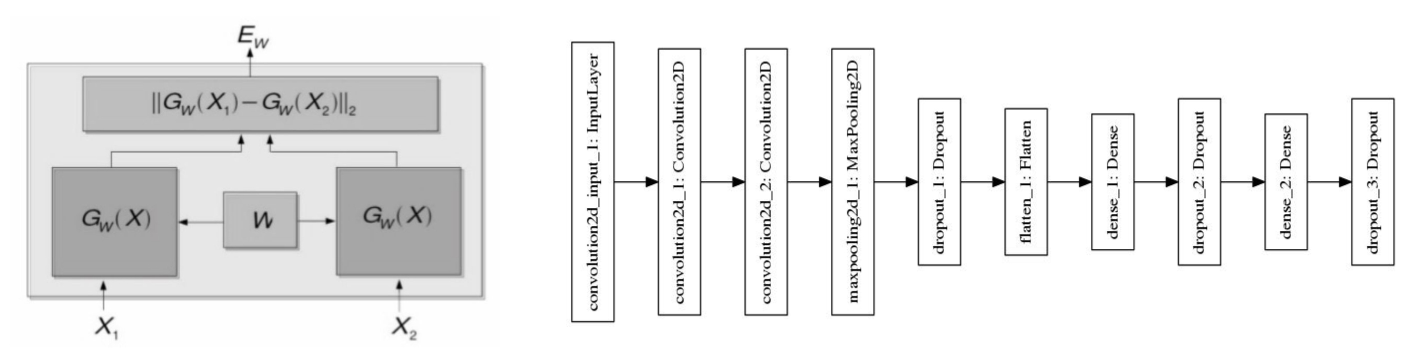



Algorithm:
- Extract features from VGGNet with default weights.
- Train fully connected classifier with extracted features to minimize categorical cross-entropy, while propogating gradient descent to last layer of VGGNet (fine-tuning).

2. **CNN + SVM:**

Algorithm:
- Extract features from fine-tuned VGGNet (obtained after running previous step).
- Train multi-class SVM on extracted features.

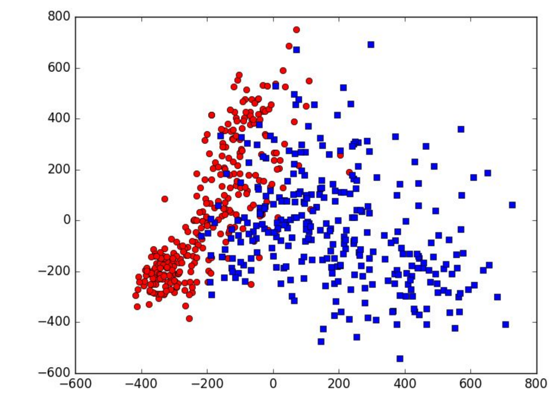
3. **Siamese Net:**



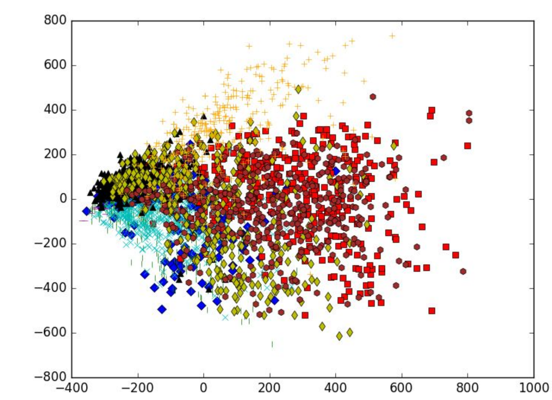

Intuition:
- Shared architecture to extract features
- Train model to minimize contrastive loss and ‘directly’ predict if two features are of same label or not.

## Results

| | Test ROC AUC | Test F1 | Test Accuracy | Test Precision | Test Recall |
|---|---|---|---|---|---|
| CNN + NN* | 0.547 | 0.671 | 0.547 | 0.526 | 0.925 |
| CNN + SVM | 0.867 | 0.882 | 0.867 | 0.793 | 0.993 |
| Siamese Net | 0.800 | 0.833 | 0.800 | 0.714 | 1 |



tSNE on two CNN features for Rambdrandt and Picasso



tSNE on 10 random painters

## Conclusions

**Painting featurization**
It appears that CNNs can extract painter-specific features using pixel data of digital copies of paintings.

**Computationally expensive**
Although it is possible to extract painter specific features, these tasks are computationally expensive in terms of processing time, disk usage and memory footprint.

## Future Work

1. Improve model performance- hyperparameter search, larger datasets.
2. Featurize visualization- what makes a painter unique?
3. Style generators- what would Rembrandt’s portrait of you look like?

## References

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4. Hadsell, Raia, Sumit Chopra, and Yann LeCun. "Dimensionality reduction by learning an invariant mapping." 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06). Vol. 2. IEEE, 2006.