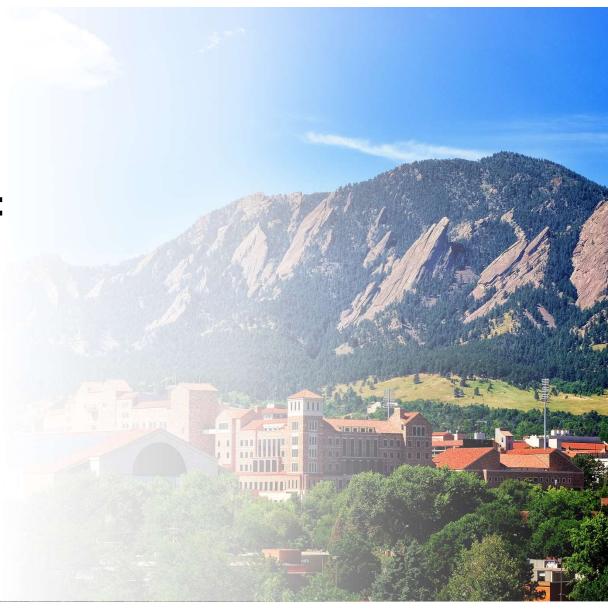
#### Fruit Image Exploration:

Dimension Reduction and Clustering Study

#### **Nick Vastine**

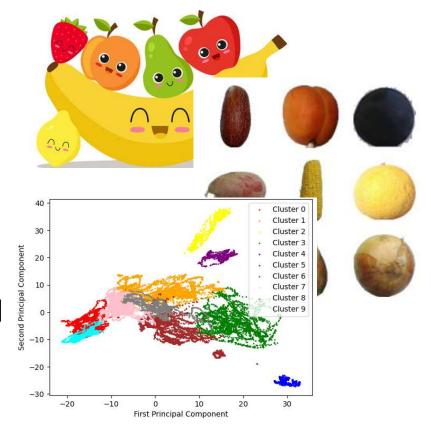
DTSA5510 – Unsupervised Algorithms in Machine Learning Final Project August 19, 2024





# **Project Topic**

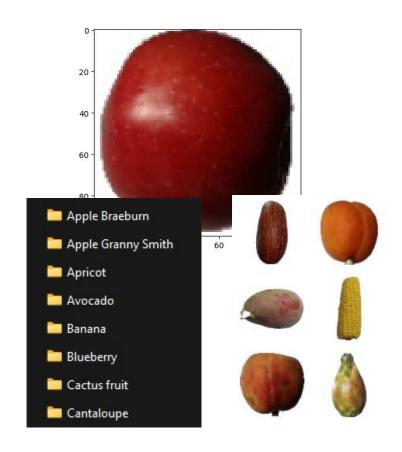
- Perform unsupervised classification of fruit images.
- Explore the effects of feature reduction, both manually and via PCA to create two models.
- Compare clustering methods and perform hyperparameter tuning on the number of clusters.





# Data / Data Cleaning

- Data is sourced from Kaggle
- 22,495 Sample Images
  - Each image is 100 pixels x 100 pixels
  - Each pixel is assigned an R,G, and B value from 0-255
  - This results in a (22495,100,100,3) sample matrix
- Each image was opened and read into the central matrix





## **Exploratory Data Analysis**

- Understanding Features
  - There are two relationships within our data
    - 1. Color value of each pixel, and therefore color of the object



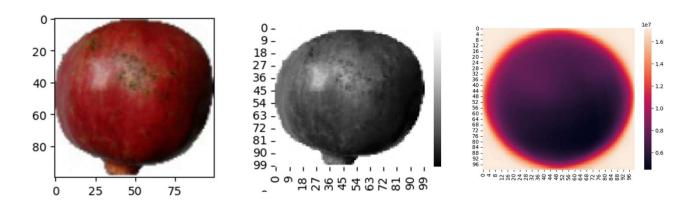
2. Shape of the object



• We could simply flatten (100,100,3) features into *30,000 features*. But that's a lot of information to digest...

# **Exploratory Data Analysis**

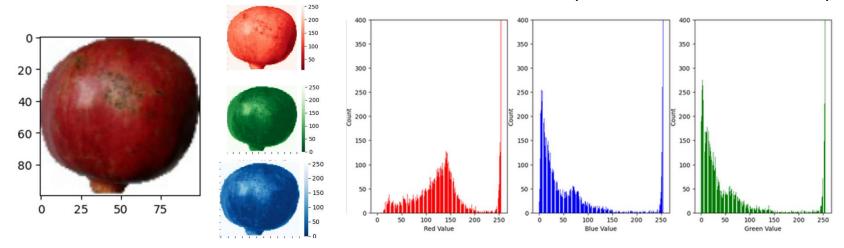
- Model 1 Intensity / Greyscale
  - Consider if we average the RGB values into a single 'intensity' value.
  - This reduces 30,000 features to *only* 10,000 features!



Note however this effectively disregards our color information...

## **Exploratory Data Analysis**

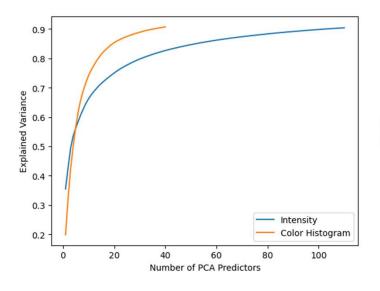
- Model 2 Color Histogram
  - Consider if take histograms of each R, G, and B value, then store those histograms as our sample feature matrix.
  - This reduces 30,000 features to 765 features! (3 colors \* 255 values).



Note however this disregards our relative position information...

# Modeling – Flattening, Scaling, PCA

- First, flatten the data into the *Intensity matrix* (22495, 10000) and process our *Color Histogram matrix* (22495, 765).
- This data is then scaled before we perform PCA.



 The PCA code determined the number of principal components to explain 90% of the variance.

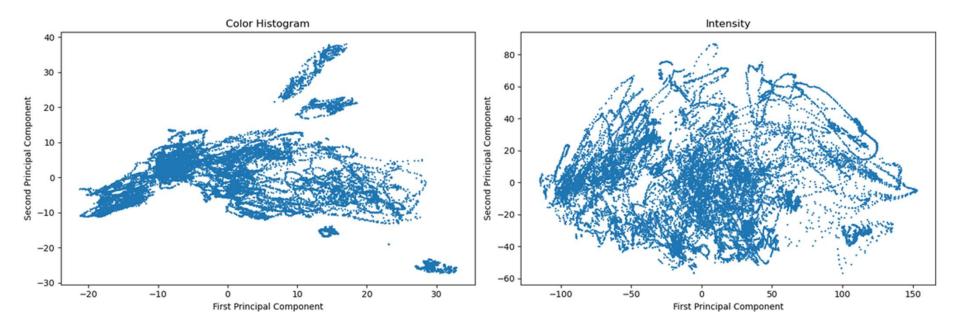
 $pca\_intensity\_mod = PCA(n\_components = 0.9, \ svd\_solver = 'full').fit(intensity\_data\_scaled) \\ pca\_color\_hist\_mod = PCA(n\_components = 0.9, \ svd\_solver = 'full').fit(color\_hist\_data\_scaled) \\ pca\_color\_hist\_mod = PCA(n\_components = 0.9, \ svd\_solver = 'full').fit(color\_hist\_data\_scaled) \\ pca\_color\_hist\_mod = PCA(n\_components = 0.9, \ svd\_solver = 'full').fit(color\_hist\_data\_scaled) \\ pca\_color\_hist\_mod = PCA(n\_components = 0.9, \ svd\_solver = 'full').fit(color\_hist\_data\_scaled) \\ pca\_color\_hist\_mod = PCA(n\_components = 0.9, \ svd\_solver = 'full').fit(color\_hist\_data\_scaled) \\ pca\_color\_hist\_mod = PCA(n\_components = 0.9, \ svd\_solver = 'full').fit(color\_hist\_data\_scaled) \\ pca\_color\_hist\_mod = PCA(n\_components = 0.9, \ svd\_solver = 'full').fit(color\_hist\_data\_scaled) \\ pca\_color\_hist\_mod = PCA(n\_components = 0.9, \ svd\_solver = 'full').fit(color\_hist\_data\_scaled) \\ pca\_color\_hist\_mod = PCA(n\_components = 0.9, \ svd\_solver = 'full').fit(color\_hist\_data\_scaled) \\ pca\_color\_hist\_mod = PCA(n\_components = 0.9, \ svd\_solver = 'full').fit(color\_hist\_data\_scaled) \\ pca\_color\_hist\_mod = PCA(n\_components = 0.9, \ svd\_solver = 'full').fit(color\_hist\_data\_scaled) \\ pca\_color\_hist\_mod = PCA(n\_components = 0.9, \ svd\_solver = 'full').fit(color\_hist\_data\_scaled) \\ pca\_color\_hist\_mod = PCA(n\_components = 0.9, \ svd\_solver = 'full').fit(color\_hist\_data\_scaled) \\ pca\_color\_hist\_mod = PCA(n\_components = 0.9, \ svd\_solver = 'full').fit(color\_hist\_data\_scaled) \\ pca\_color\_hist\_mod = PCA(n\_components = 0.9, \ svd\_solver = 'full').fit(color\_hist\_data\_scaled) \\ pca\_color\_hist\_mod = PCA(n\_components = 0.9, \ svd\_solver = 'full').fit(color\_hist\_data\_scaled) \\ pca\_color\_hist\_mod = PCA(n\_components = 0.9, \ svd\_solver = 'full').fit(color\_hist\_data\_scaled) \\ pca\_color\_hist\_mod = PCA(n\_components = 0.9, \ svd\_solver = 'full').fit(color\_hist\_data\_scaled) \\ pca\_color\_hist\_mod = PCA(n\_components = 0.9, \ svd\_solver = 'full').fit(color\_hist\_scaled) \\ pca\_color\_hist\_mod = PCA(n\_components = 0.9, \ svd\_solver = 'full').fit(color\_hist\_scaled)$ 

 This analysis found the Color Histogram model required 40 components, while Intensity required more than 100.



# Modeling – PCA (cont.)

 We can also visualize how the first two principal components work to separate our data into possible clusters for each model.

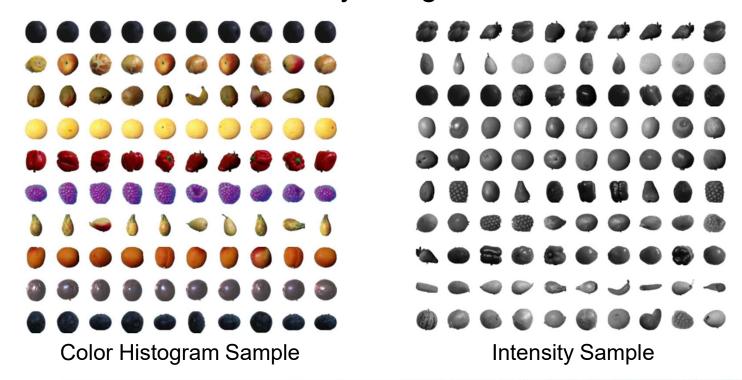




Fruit Clustering

### **Modeling – Reduction Comparison**

We will first evaluate arbitrarily using 10 clusters.





### Modeling – 33 Clusters

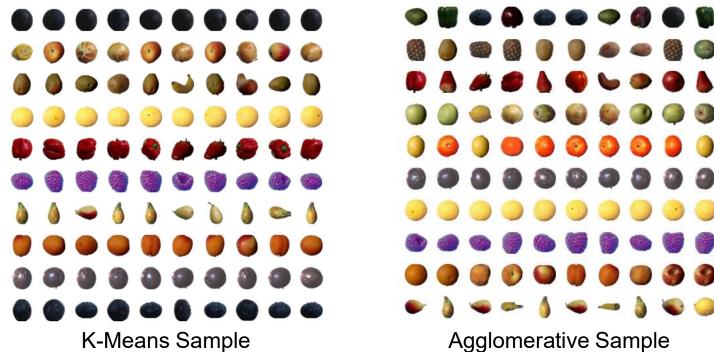
• We know there are 33 categories from the training data.



33 Cluster Color Histogram Sample

### **Modeling – Method Comparison**

We can compare methods for our color histogram dataset

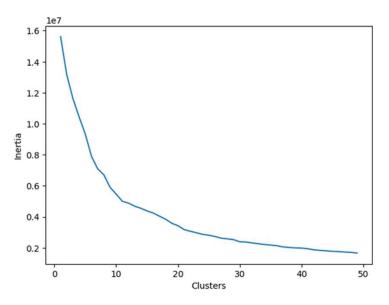


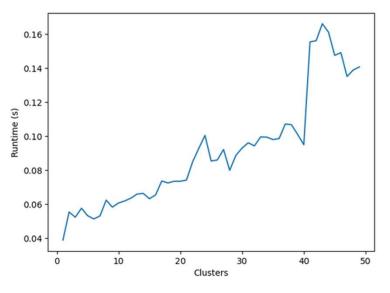




# Modeling – Hyperparameter Tuning

- Below evaluates our color histogram K-means across a range of clusters, comparing inertia and runtime.
  - Note the 'elbow' at 10 clusters, conveniently matching our analysis.

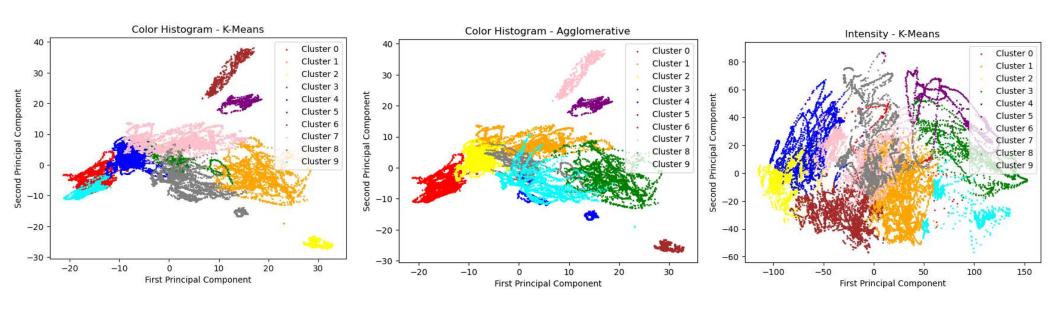






# **Modeling – Method Comparison**

We can compare based on our principal components as well





## Results & Analysis Summary

- Dimension Reduction is inherently a sacrifice in resolution
  - Using a mix of approaches can dramatically reduce features (from 30,000 to 765 to 40 for the color histogram)
  - There are tradeoffs (ex. loss of color information for intensity analysis)
- It is valuable to visualize and contextualize your response
  - In this case, an imagery problem makes results easy to interpret.
  - PCA analysis plots are valuable to anticipate clusters, or if data is suitable for a clustering application
- K-Means runs significantly faster than Agglomerative Clustering



#### **Discussion & Conclusion**

- Key takeaway is the importance of experimentation, appropriate feature reduction, and evaluation procedures.
- There is such thing as too much data (curse of dimensionality)
  - Was unable to perform PCA on the flattened original dataset
- Future Improvements
  - Structure the analysis for supervised learning, using the labeled training set to calculate accuracy for 33 categories
  - Consider applying IncrementalPCA when there are too many features
  - Explore the effects of reduced datasets on clustering effectiveness



Thank you for listening!

Fruit Image Exploration:

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