

# Capstone project



*Hitting the top notes*

Modeling on  
fragrance notes to  
classify ratings

**Allison Bishop**

# Background - My motivation

## CHERRIES—IN GENERAL

**Season:** late spring–late summer

**Taste:** sweet

**Weight:** light–medium

**Volume:** moderate

**Techniques:** flambé, poach, raw, stew

### Flavor Affinities

cherries + almonds + cream + kirsch + vanilla

cherries + chocolate + walnuts

cherries + coconut + custard

cherries + coffee + cream

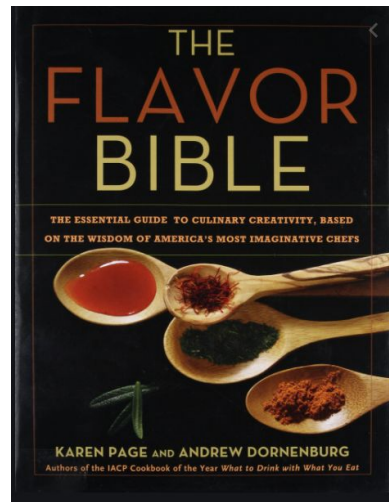
cherries + goat cheese + ice wine vinegar + black pepper + thyme

cherries + honey + pistachios + yogurt

cherries + mint + vanilla

cherries + orange + sugar + dry red wine

cherries + sweet vermouth + vanilla



# Background - Classes of notes

**Top:** Form initial impression. Selling point.

High volatility.

*Light, bright (like citrus fruits)*

**Middle:** Forms the body. 40-80% of total aroma.

Midrange volatility.

*Complex, midweight (like florals)*

**Base:** Foundation of fragrance. Brings depth.

Low volatility.

*Deep, heavyweight (like sandalwood)*



# Preprocessing - Dummify notes

*Before*

	title	0	1	2	3
0	Aamal The Spirit of Dubai for women and men	Top0Turkish Rose	Top1Bulgarian Rose	Top2Bergamot	Top3Fruits
1	Aatifa Ajmal for women and men	Top0Nutmeg	Top1Rose	Top2Cumin	Middle0Amber



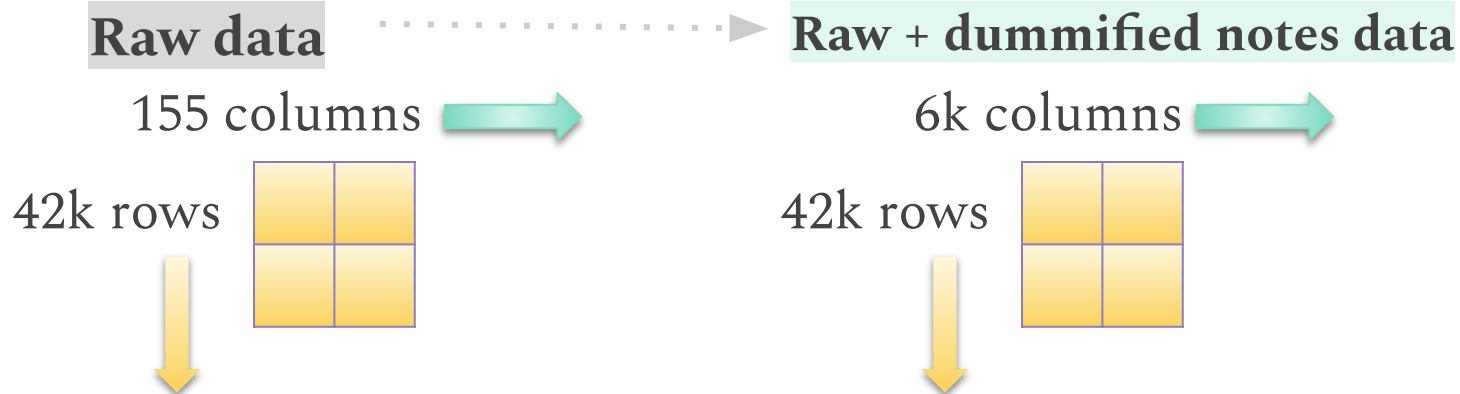
*After*

top_0_mandarin_orange	top_1_green_apple	top_2_thyme	middle_0_2_lavender
1	1	1	1

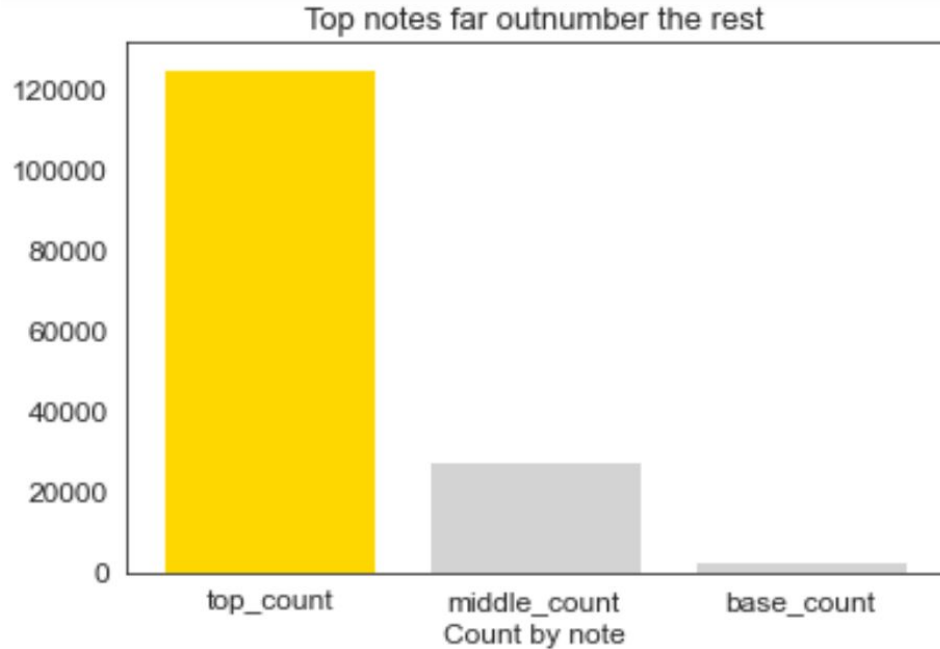


# Preprocessing - Results

**The dataset drastically changed shape**



# Data profile - Top, middle, base notes



Abundance of  
top notes data

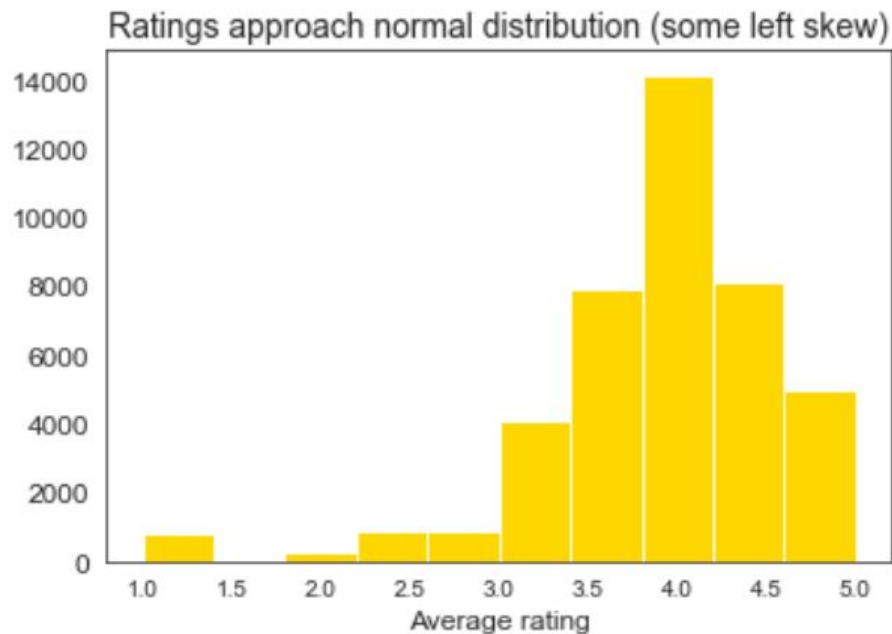


Project focus



Quick hit (*top*) only

# Data profile - Average ratings

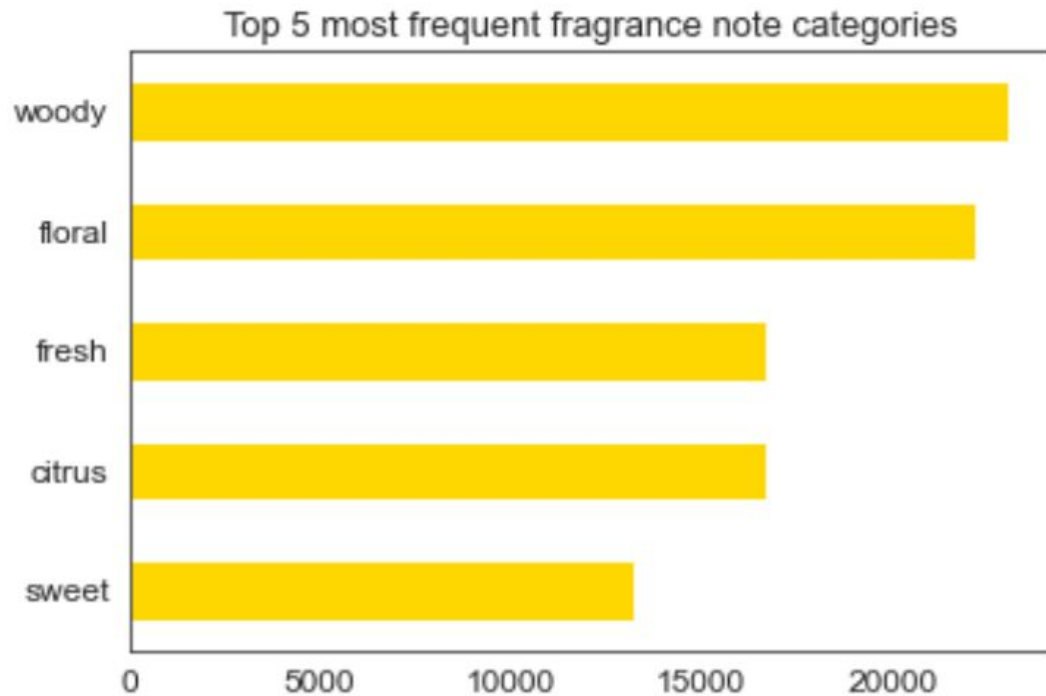


After binning,  
modeled just on  
ratings 3 and 4



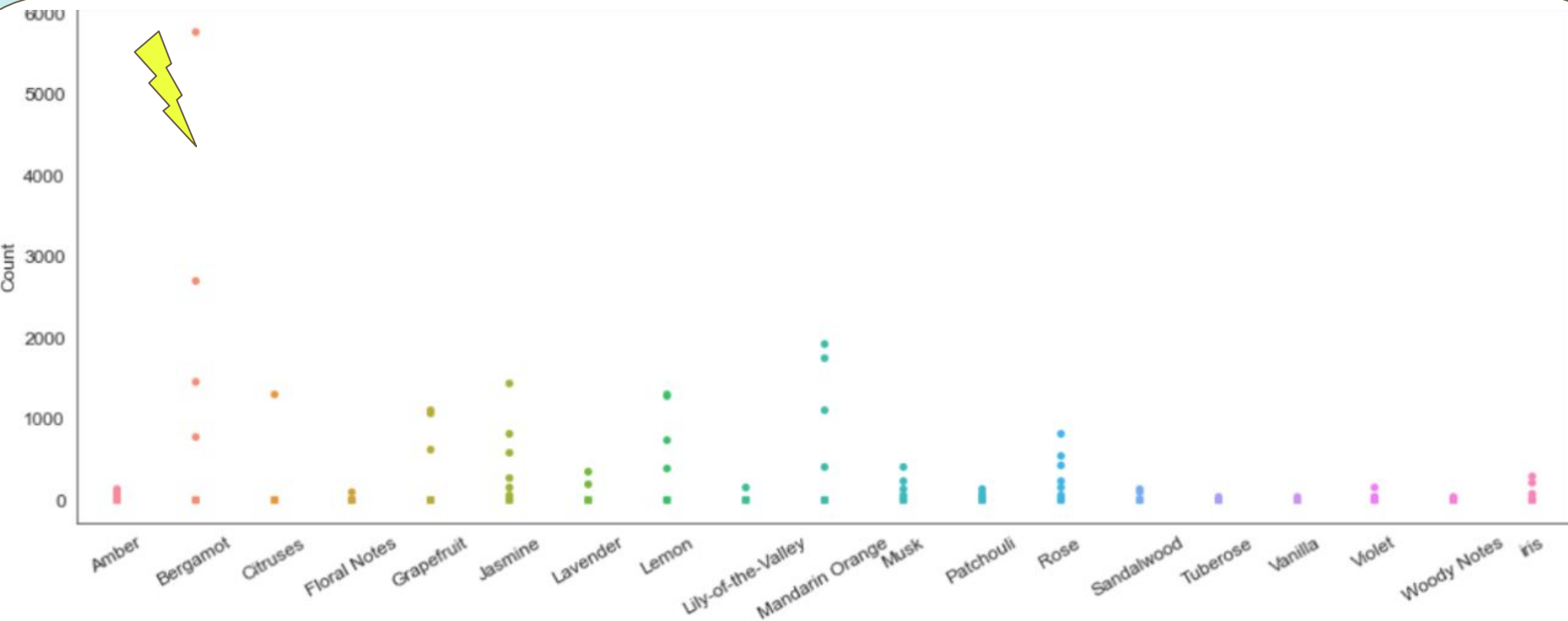


# EDA - Fragrance notes





# EDA - Counts of most frequently used notes



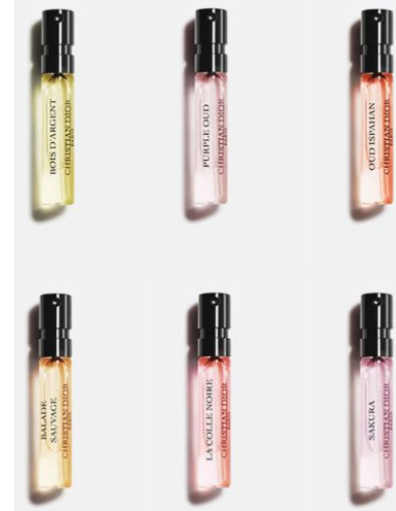
# Sampling of data science methods

*A bit like sampling fragrances!*

Logistic regression (inference + predictions)

Tree-based modeling (inference)

Clustering (inference)



# Modeling results - Accuracy scores

Logistic regression  
with and without  
Principal Component Analysis (PCA)

Baseline = 54%

Majority class = Rating 4

With PCA

Train set: 70.2%

Test set: 56.4%

80 components

Without PCA

Train set: 70.2%

Test set: 54.7%

# Modeling results - Accuracy scores

## Tree-based models

### Decision tree

### Random Forest + GridSearchCV

Baseline model = 54%

Majority class = Rating 4

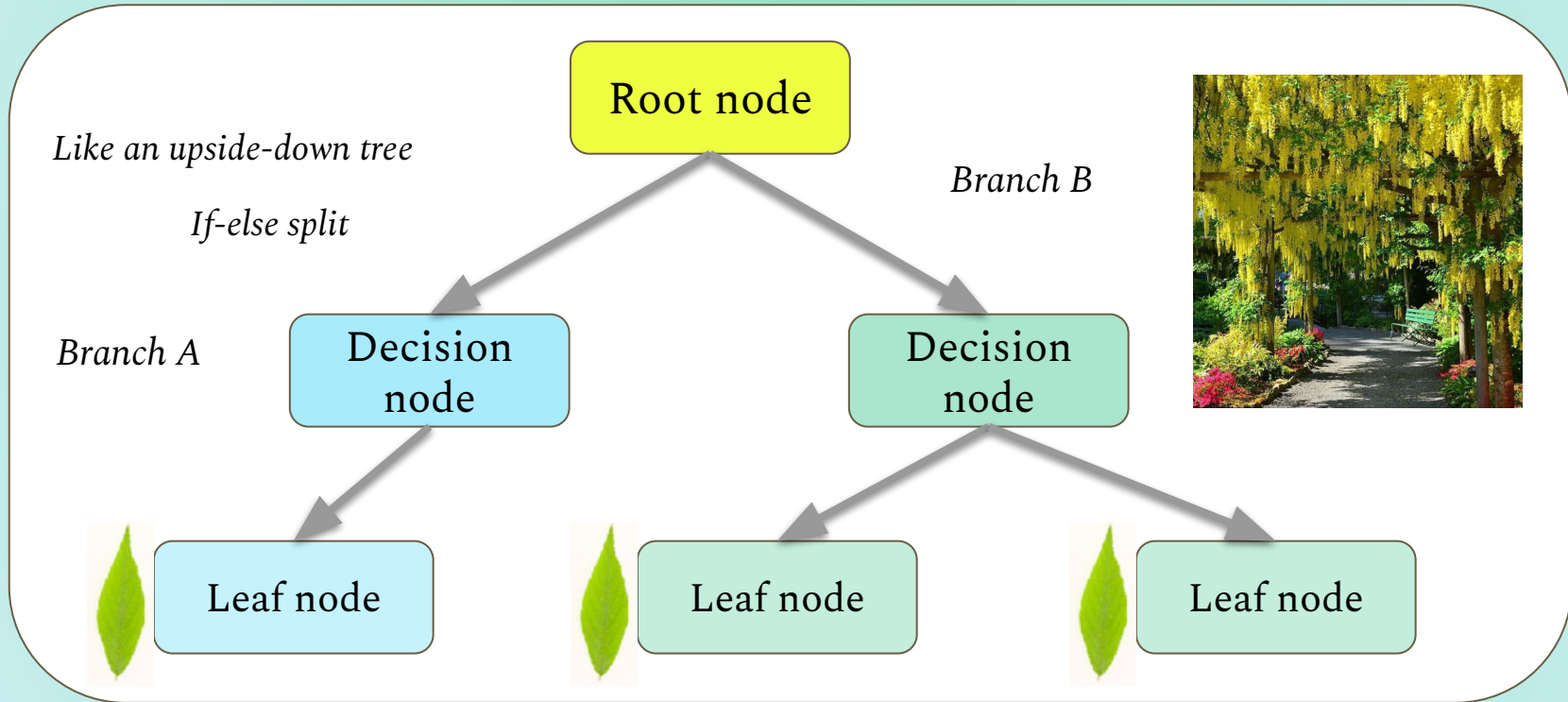
Train set: 92%

Test set: 54%

Train set: 92%

Test set: 60%

# Modeling: Anatomy of a decision tree

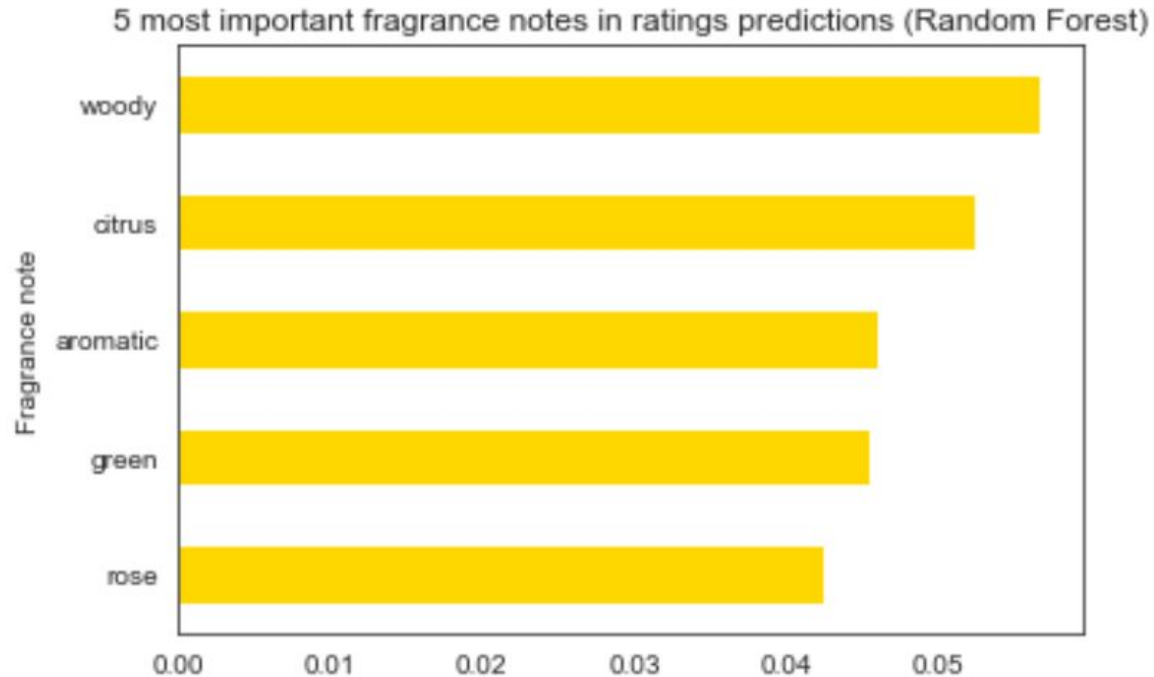


# Modeling: Decision tree

```
|--- fruity <= 0.50  
|   |--- honey <= 0.50  
|   |   |--- patchouli <= 0.50  
|   |   |   |--- earthy <= 0.50  
|   |   |   |   |--- balsamic <= 0.50  
|   |   |   |   |   |--- tonka (coumarin) <= 0.50  
|   |   |   |   |   |   |--- fresh spicy <= 0.50  
|   |   |   |   |   |   |   |--- herbal <= 0.50  
|   |   |   |   |   |   |   |   |--- vanilla <= 0.50  
|   |   |   |   |   |   |   |   |   |--- powdery <= 0.50  
|   |   |   |   |   |   |   |   |   |   |--- warm spicy <= 0.50
```

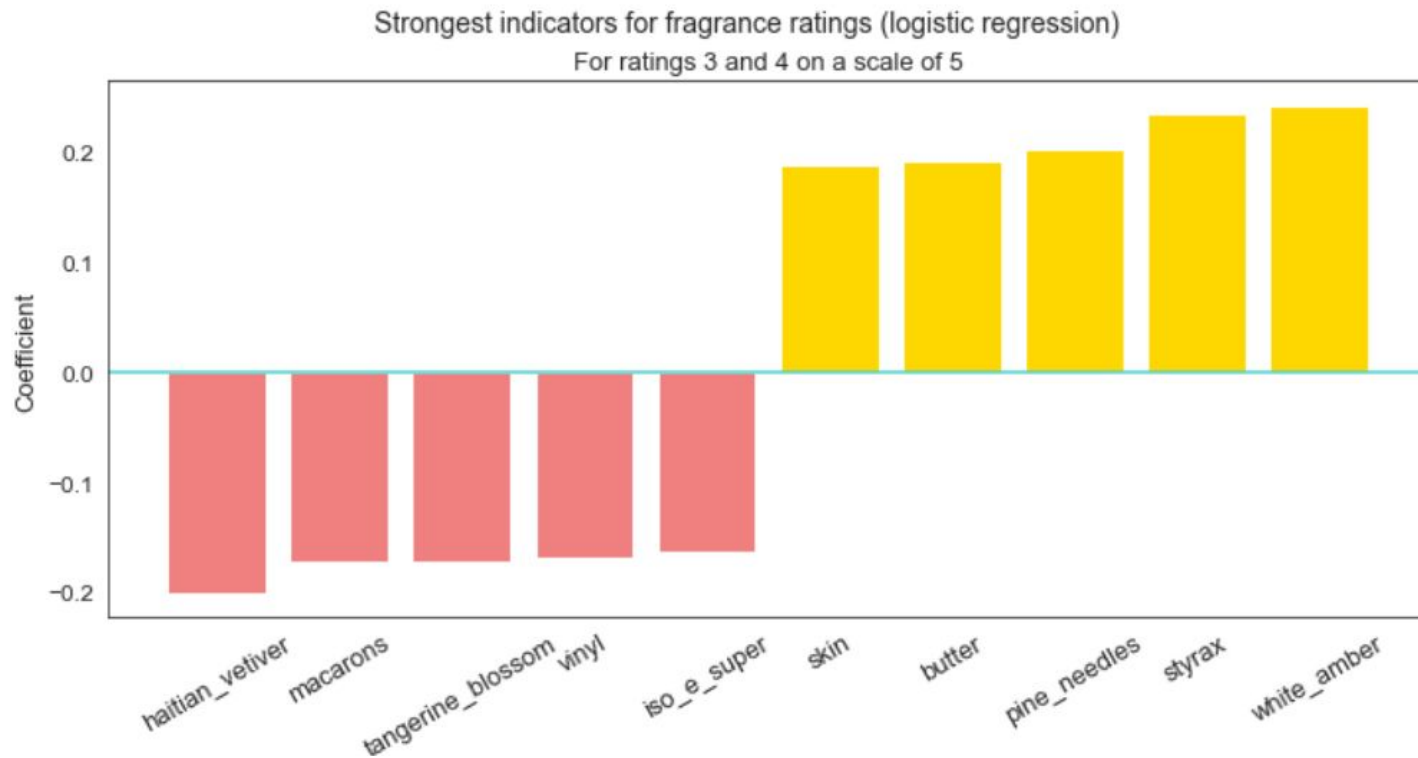


# Modeling results: What we can infer





# Modeling results: What we can infer



# Clustering - Results

## Silhouette score

Cohesion (*intra-cluster distance*) - separation (*inter-cluster distance*)

Range: -1 (worst) to 1 (best)

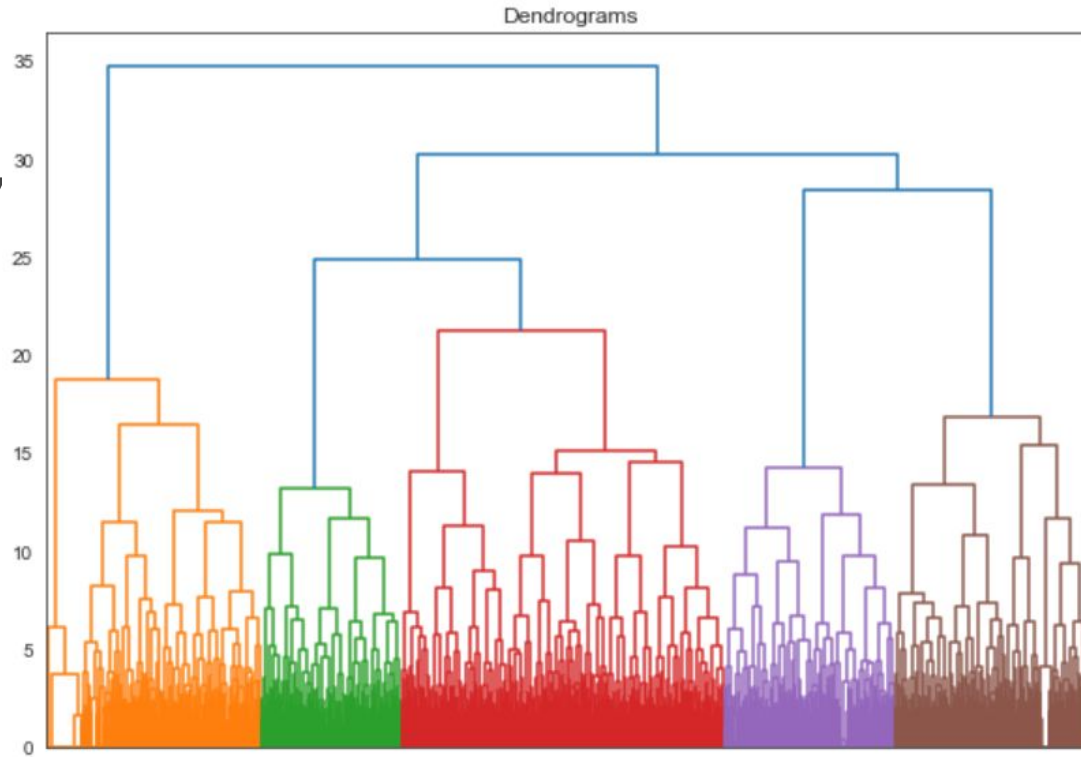
DBSCAN

Silhouette score: -0.3

KMeans

Silhouette score: -0.2

# Clustering - Next steps



Feature  
agglomeration  
+  
Hierarchical  
clustering

# Next steps (seriously)

Recommender system for product development

Live data stream

Now, a quick demo!

