



FASHION PREDICTION

[Login](#)[INTRODUCTION](#)[MOTIVATION](#)[SETTING STAGE](#)[CORE ANALYSIS](#)[CONCLUSION](#)

PREDICTING FASHION STYLES



Are you looking for an outer or even accessories that have streetwear style?

Look no other! We dedicated our ideas to getting you a perfect fit for daily activities!

[About us](#)

Bucket Hat

Long Knitwear

Sleeveless Puffer Jacket

Striped Long Shirt

Knitted Cardigan



FASHION PREDICTION



Login

INTRODUCTION

MOTIVATION

SETTING STAGE

CORE ANALYSIS

CONCLUSION



RITHIKA MURUGAN

PREDICTING COLOUR AND STYLE ATTRIBUTES IN THE FASHION INDUSTRY.



S. SHANTHOSH

AGE

PRICE

CATEGORY

COLOUR

RATING

STYLE ATTRIBUTE

WHAT WE AIM TO SOLVE





FASHION PREDICTION

[Login](#)[INTRODUCTION](#)[MOTIVATION](#)[SETTING STAGE](#)[CORE ANALYSIS](#)[CONCLUSION](#)

The collage consists of five screenshots arranged in a grid-like pattern:

- Top Left:** Amazon homepage featuring a promotional banner for the TV show "FROM" and sections for "The dress edit", "Warm weather deals in Plus fashion", and "Try new shirts for free".
- Top Middle:** eBay search results for "Women's Luxury Fashion", showing a grid of luxury clothing items.
- Bottom Left:** A mobile screenshot of the lavish alice website, displaying three main categories: "new arrivals", "party wear", and "suiting", each with a woman modeling an outfit.
- Bottom Middle:** A screenshot of a shopping app interface titled "SHOPPING", showing a woman smiling and a grid of products including a "Black Backpack" and a "White Hat".
- Bottom Right:** A screenshot of the ModCloth website, featuring a "DRESS SALE ON SALE" banner with "EXTRA 50% OFF" and a woman modeling a blue dress.

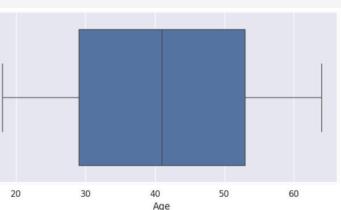
- GROWING IMPORTANCE OF DATA-DRIVEN DECISION-MAKING IN FASHION
- SHIFT TOWARDS ONLINE SHOPPING EMPHASIZES NEED FOR ACCURATE TREND PREDICTION
- GOAL: DEVELOP MACHINE LEARNING MODELS TO ASSIST IN PRODUCT DESIGN
- OBJECTIVE: INCREASE SUCCESS RATE OF FASHION PRODUCTS



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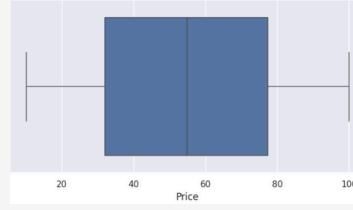
[Login](#)[INTRODUCTION](#)[MOTIVATION](#)[SETTING STAGE](#)[CORE ANALYSIS](#)[CONCLUSION](#)

```
#visualisation for numeric variables  
#age  
f, axes = plt.subplots(1, 2, figsize=(18, 4))  
sb.boxplot(data = salesdata['Age'], orient = "h", ax = axes[0])  
sb.histplot(data = salesdata['Age'], ax = axes[1])  
  
<Axes: xlabel='Age', ylabel='Count'>
```



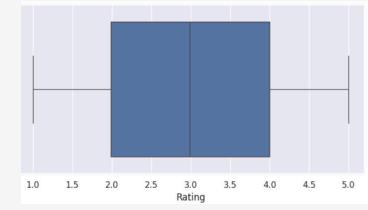
AGE OF ALL
VARIABLES
ARE FAIRLY
DISTRIBUTED

```
#visualisation for Price  
f, axes = plt.subplots(1, 2, figsize=(18, 4))  
sb.boxplot(data = salesdata['Price'], orient = "h", ax = axes[0])  
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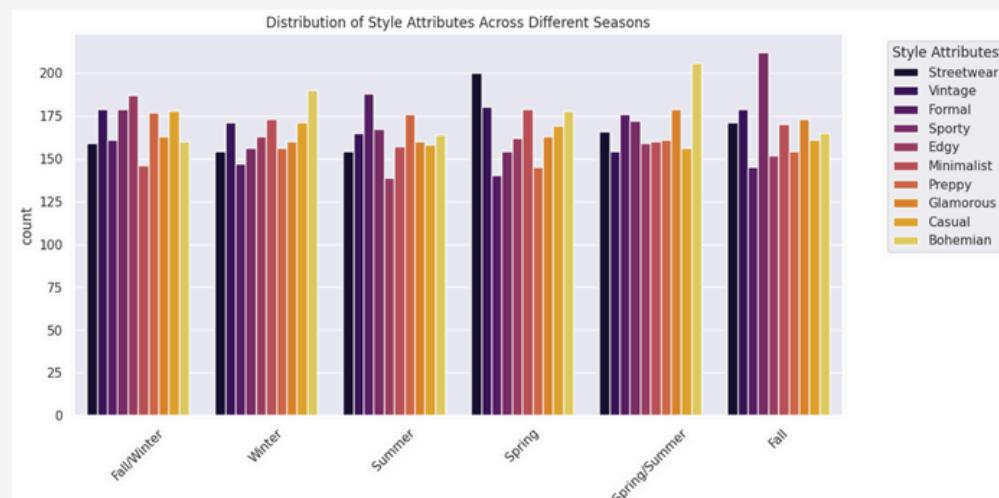
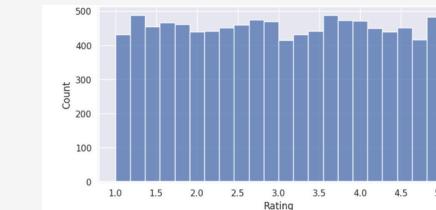
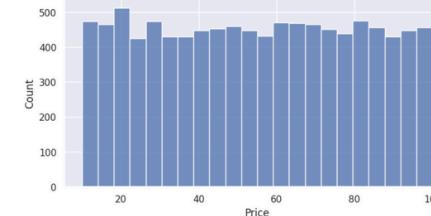
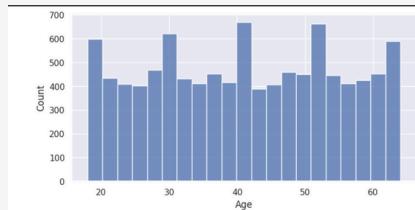


DEMAND FOR
ALL
PRICEPOINTS
OF PRODUCTS.

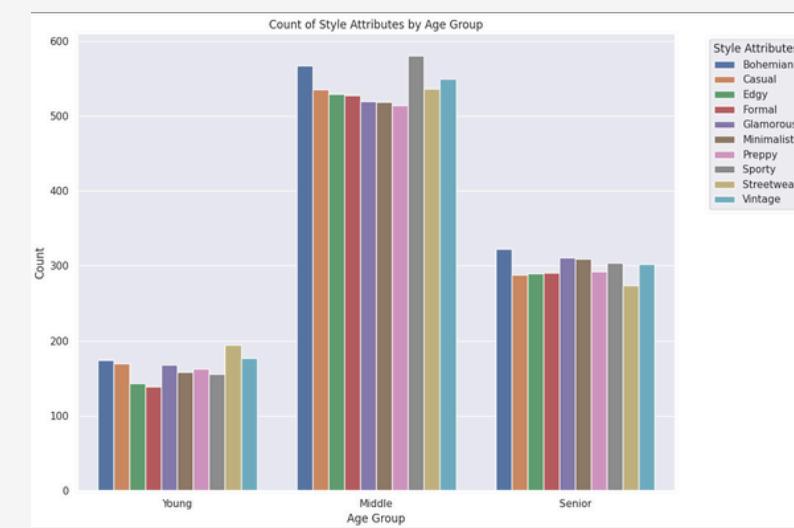
```
#visualization for rating  
f, axes = plt.subplots(1, 2, figsize=(18, 4))  
sb.boxplot(data = salesdata['Rating'], orient = "h", ax = axes[0])  
sb.histplot(data = salesdata['Rating'], ax = axes[1])  
  
<Axes: xlabel='Rating', ylabel='Count'>
```



RATINGS
ARE ALSO
FAIR



WITHIN
SEASON

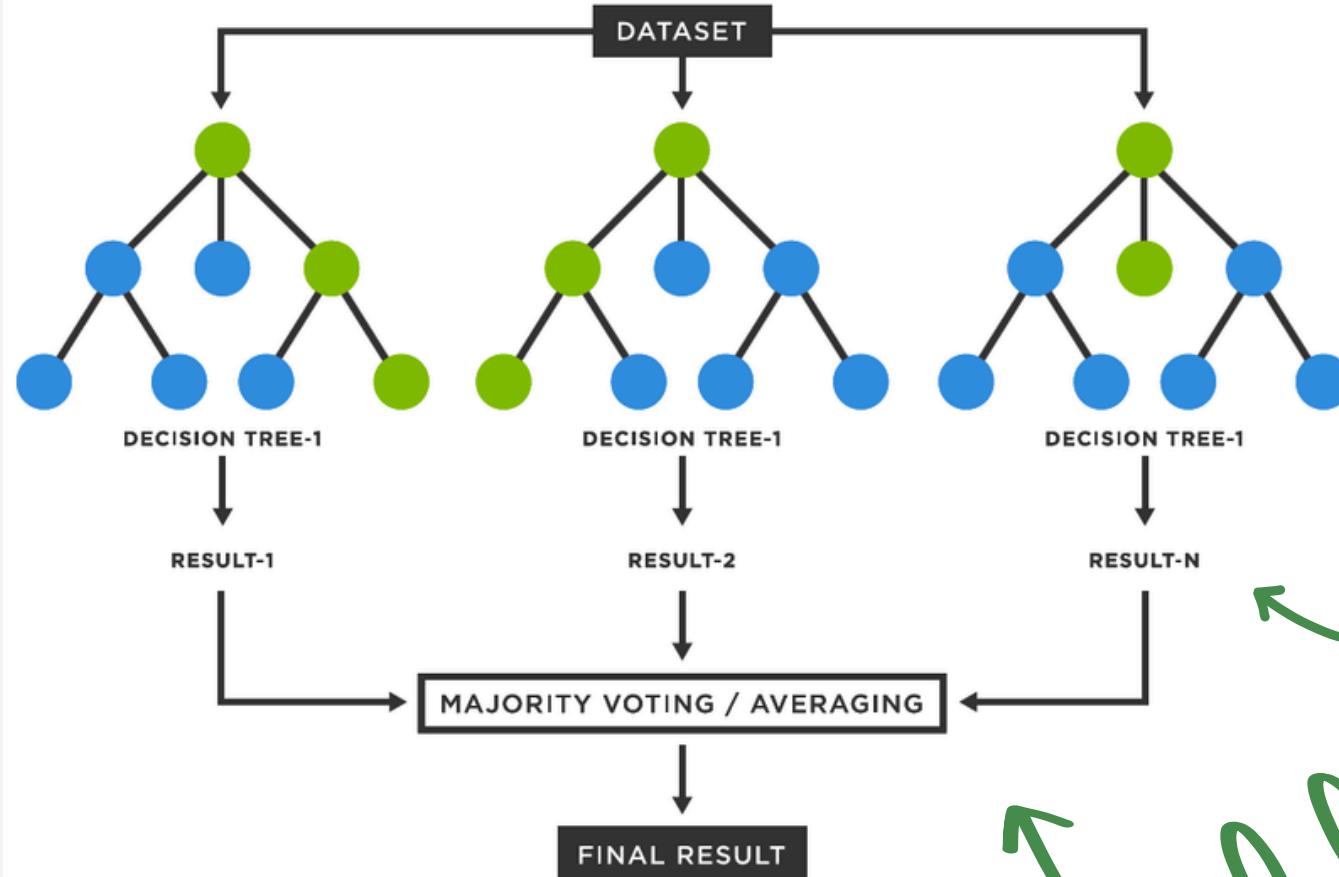


WITHIN
AGE



[INTRODUCTION](#)[MOTIVATION](#)[SETTING STAGE](#)[CORE ANALYSIS](#)[CONCLUSION](#)

RANDOM FOREST



CONSTRUCTS SEVERAL DECISION TREES

EACH TREE MAKES IT'S OWN PREDICTION

**REDUCES ERRORS BY
AGGREGATING PREDICTIONS FROM
MULTIPLE TREES**

[INTRODUCTION](#)[MOTIVATION](#)[SETTING STAGE](#)[CORE ANALYSIS](#)[CONCLUSION](#)

AGE-BASED SPLIT

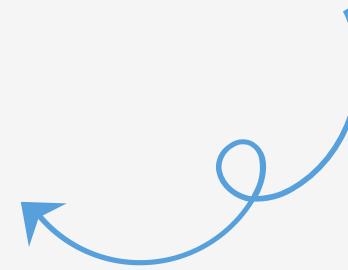
AGE-SPECIFIC VARIATIONS
MIGHT NOT BE SUFFICIENTLY
CAPTURED BY THE MODEL

Accuracy for age-based split: 8.68%



9.35%

FOR THE GENERAL MODEL



SEASON-BASED SPLIT

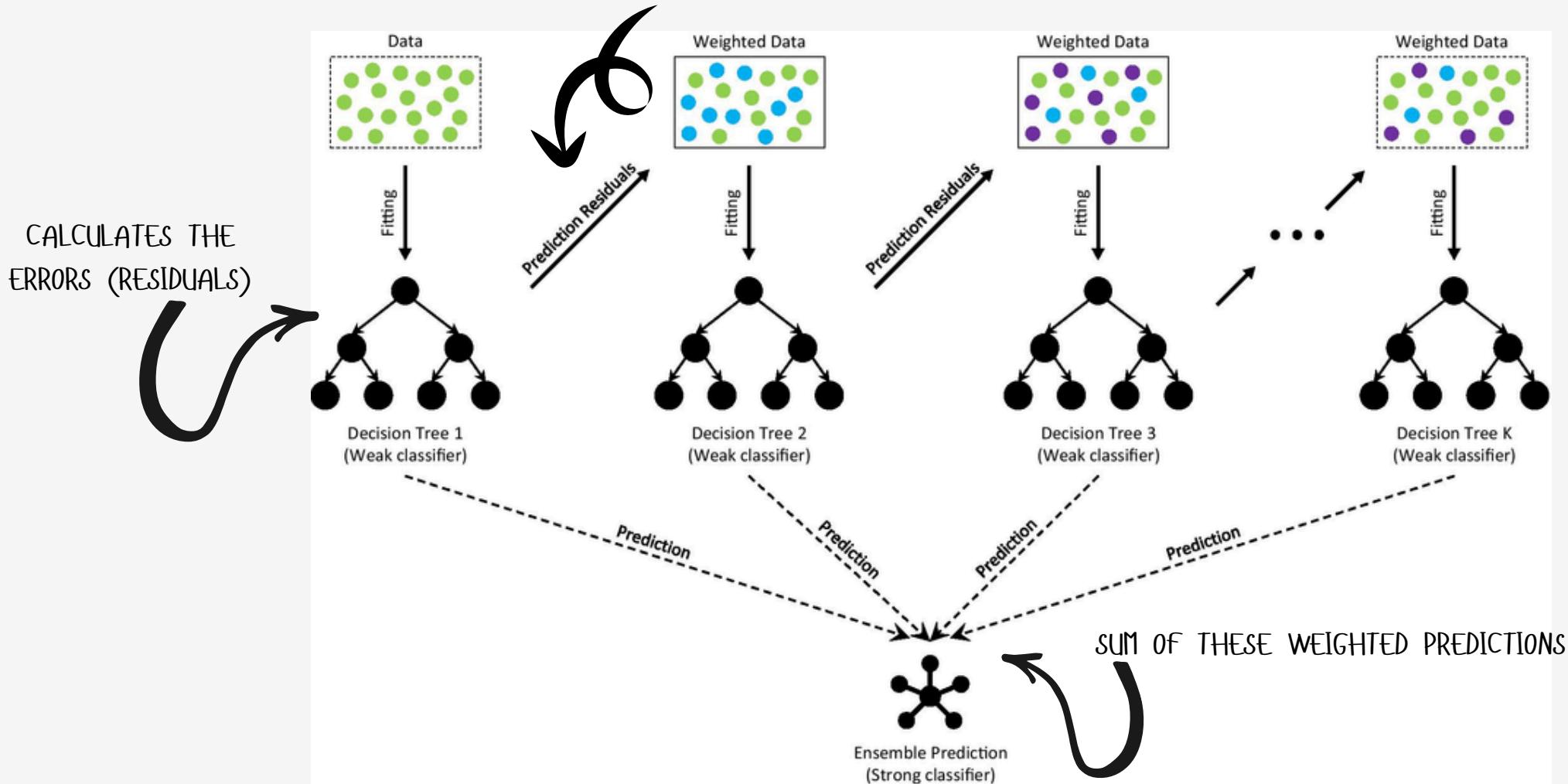
WHILE SEASONALITY IMPACTS STYLE,
THE FEATURES AND THEIR
INTERACTIONS CAPTURED BY THE
RANDOM FOREST TREES MIGHT NOT
ALIGN WELL

accuracy for Season-Based Split: 8.57%

[INTRODUCTION](#)[MOTIVATION](#)[SETTING STAGE](#)[CORE ANALYSIS](#)[CONCLUSION](#)

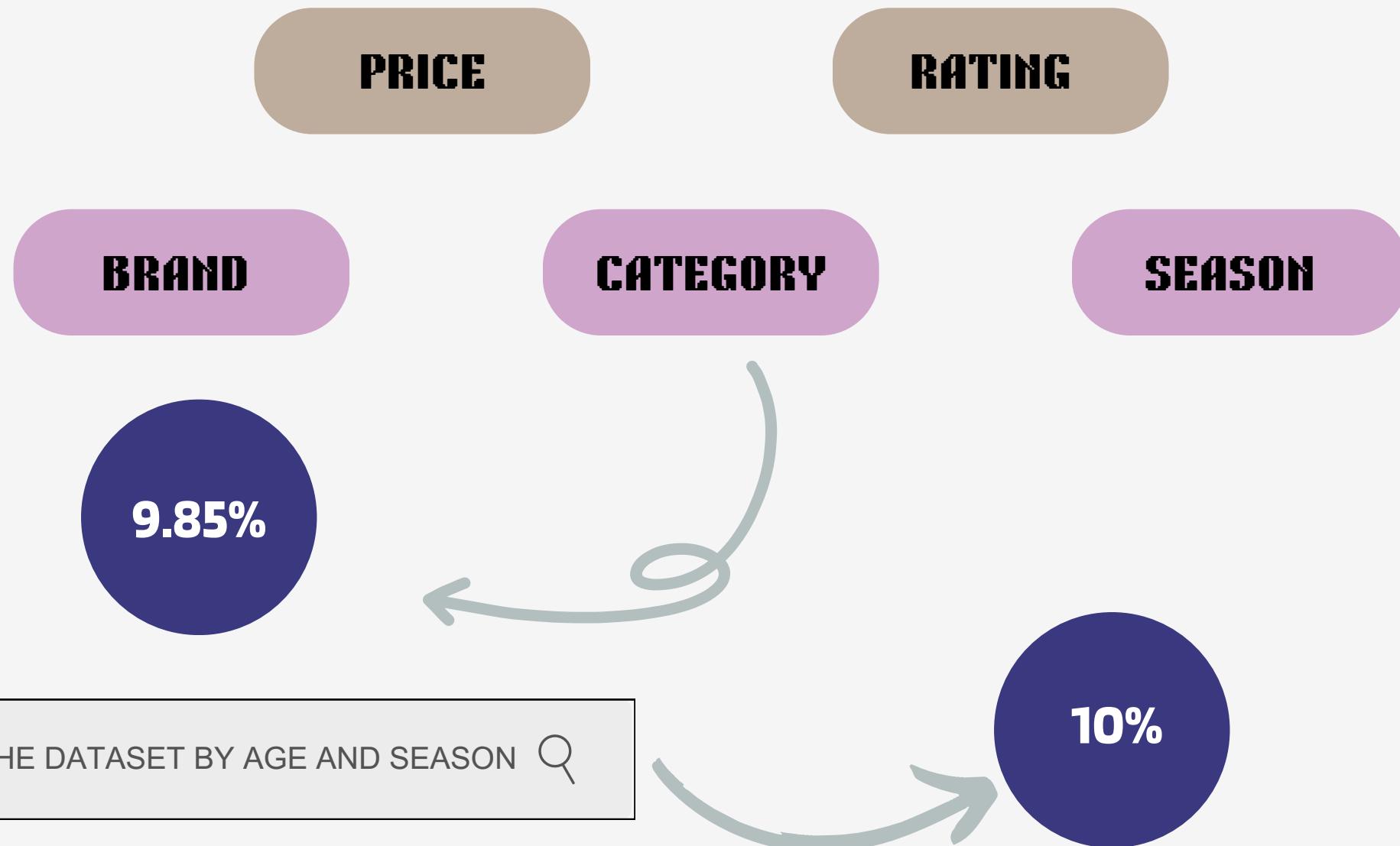
GRADIENT BOOSTER

SUBSEQUENT MODELS FOCUS ON CORRECTING THESE
ERRORS BY PREDICTING THE RESIDUALS



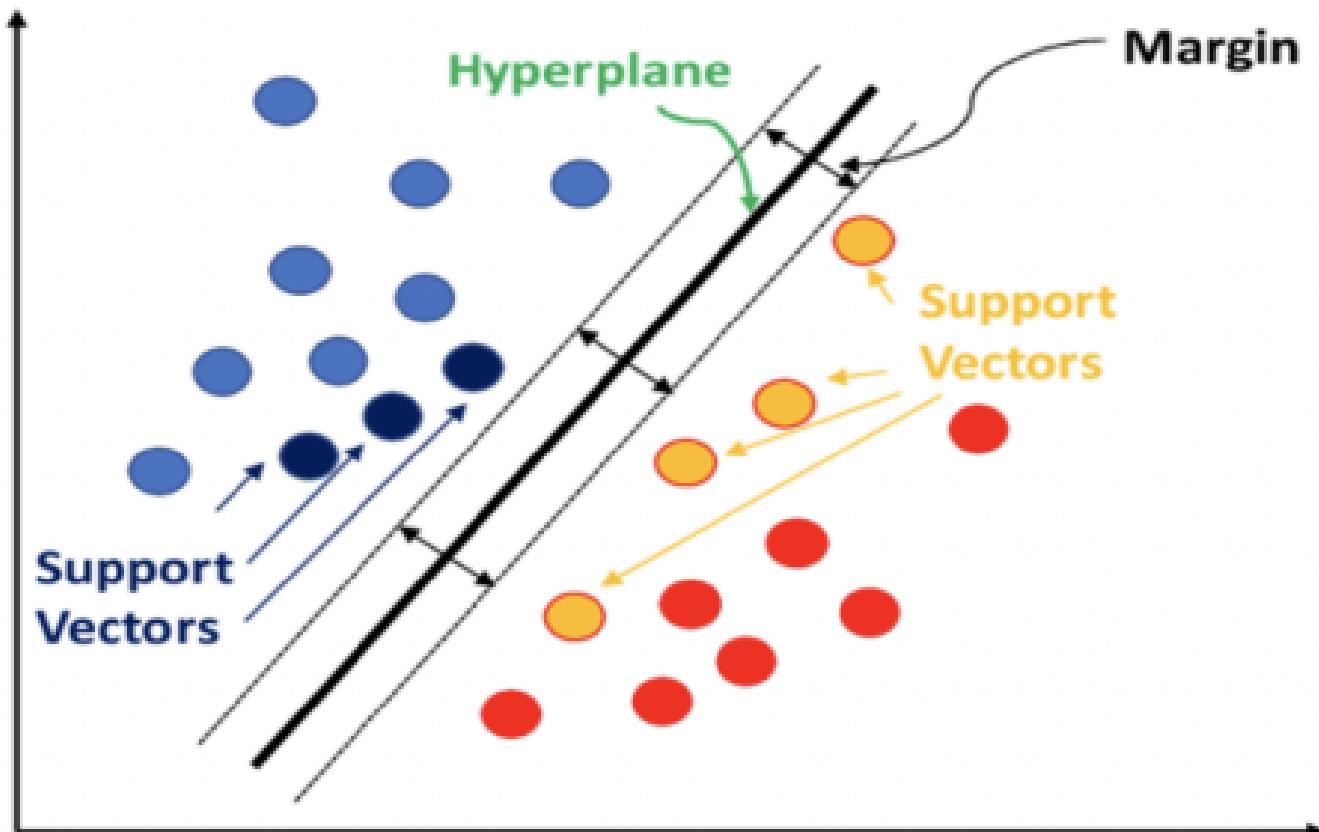


FASHION PREDICTION

[Login](#)[INTRODUCTION](#)[MOTIVATION](#)[SETTING STAGE](#)[CORE ANALYSIS](#)[CONCLUSION](#)

[INTRODUCTION](#)[MOTIVATION](#)[SETTING STAGE](#)[CORE ANALYSIS](#)[CONCLUSION](#)

SUPPORT VECTOR MODEL



- HYPER PLANE DISTINCTLY CLASSIFIES THE DATA POINTS.
- MAXIMIZING THE MARGIN BETWEEN THE DATA POINTS OF DIFFERENT CLASSES
- FOR NON-LINEAR BOUNDARIES, SVM USES KERNELS TO TRANSFORM DATA INTO HIGHER DIMENSIONS
- HANDLING OUTLIERS AND MAXIMIZING THE MARGIN
- TRAINING PROCESS INVOLVES SOLVING A CONSTRAINED OPTIMIZATION PROBLEM



FASHION PREDICTION



Login

INTRODUCTION

MOTIVATION

SETTING STAGE

CORE ANALYSIS

CONCLUSION

SVM

HANDLES DIFFERENT DATA TYPES

IMPROVEMENT WITH KERNELS

AGE-SPECIFIC
FEATURES
SIGNIFICANTLY
INFLUENCE STYLE
PREFERENCES

accuracy for general model: 9.95%

NDICATES
CHALLENGES IN
CAPTURING THE
COMPLEXITIES

accuracy for Age-Based Split: 13.54%

SEASONAL VARIATIONS,
WHICH OFTEN INFLUENCE
FASHION TRENDS
SIGNIFICANTLY, WERE
BETTER CAPTURED WITH
TARGETED SVM MODELS.

accuracy for Season-Based Split: 11.24%

[INTRODUCTION](#)[MOTIVATION](#)[SETTING STAGE](#)[CORE ANALYSIS](#)[CONCLUSION](#)

MODEL CHALLENGES



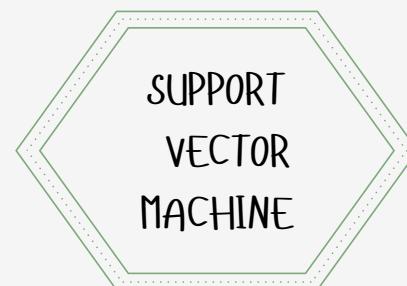
9.85%

NOISY AND COMPLEX
NATURE OF FASHION DATA.



9.35%

FAILING DUE TO ITS ENSEMBLE
NATURE.

9.95% -
13.54%

SVMS MANAGED BETTER WITH NON-
LINEAR DECISION BOUNDARIES BUT
STILL FELL SHORT OF HIGH ACCURACY.





FASHION PREDICTION

[Login](#)[INTRODUCTION](#)[MOTIVATION](#)[SETTING STAGE](#)[CORE ANALYSIS](#)[CONCLUSION](#)

[INTRODUCTION](#)[MOTIVATION](#)[SETTING STAGE](#)[CORE ANALYSIS](#)[CONCLUSION](#)

REASONS FOR MODEL LIMITATIONS

- INADEQUATE FEATURE REPRESENTATION
- MODEL ASSUMPTIONS

RECOMMENDATIONS FOR IMPROVEMENT

- DEEP LEARNING
- ADVANCED FEATURE ENGINEERING
- HYBRID MODELS



[INTRODUCTION](#)[MOTIVATION](#)[SETTING STAGE](#)[CORE ANALYSIS](#)[CONCLUSION](#)

THANK
YOU!!

