



# 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

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

RITHIKA MURUGAN

## PREDICTING COLOUR AND STYLE ATTRIBUTES IN THE FASHION INDUSTRY.



S. SHANTHOSH

### FDAE

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:** An Amazon homepage featuring a promotional banner for a TV show and sections for "The dress edit" and "Warm weather deals in Plus fashion".
- Top Middle:** An eBay search results page for "Women's Luxury Fashion", showing various women's clothing items.
- Bottom Left:** A screenshot of the Lush Alice website, showcasing categories like "new arrivals", "partywear", and "suiting".
- Bottom Middle:** A screenshot of a shopping app interface displaying products such as "Black Backpack" and "White Hat".
- Bottom Right:** A screenshot of the ModCloth website, highlighting a "DRESS SALE ON SALE" and "EXTRA 50% OFF" offer.

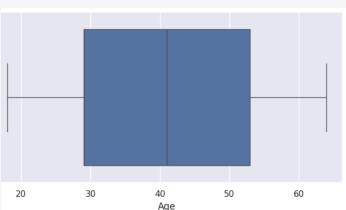
- GROWING IMPORTANCE OF DATA-DRIVEN DECISION-MAKING IN FASHION
- SHIFT TOWARDS ONLINE SHOPPING EMPHASIZES NEED FOR ACCURATE TREND PREDICTION
- GOAL: DEVELOP MACHINE LEARNING MODELS TO ASSIST IN PRODUCT DESIGN
- OBJECTIVE: INCREASE SUCCESS RATE OF FASHION PRODUCTS



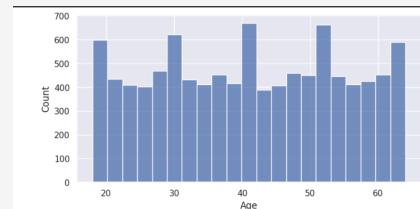
# FASHION PREDICTION

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

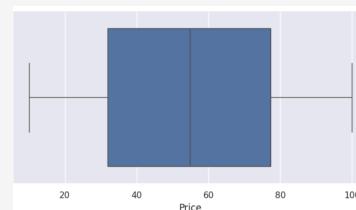
```
#visualisation for numeric variables  
#age  
f, axes = plt.subplots(1, 2, figsize=(18, 4))  
sb.boxplot(data = salesdata['Age'], orient = "h", ax = axes[0])  
sb.histplot(data = salesdata['Age'], ax = axes[1])  
  
<Axes: xlabel='Age', ylabel='Count'>
```



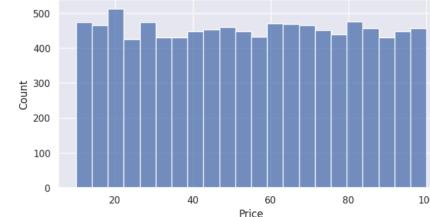
AGE OF ALL  
VARIABLES  
ARE FAIRLY  
DISTRIBUTED



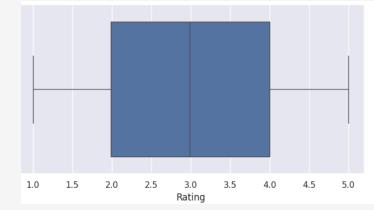
```
#visualisation for Price  
f, axes = plt.subplots(1, 2, figsize=(18, 4))  
sb.boxplot(data = salesdata['Price'], orient = "h", ax = axes[0])  
sb.histplot(data = salesdata['Price'], ax = axes[1])  
  
<Axes: xlabel='Price', ylabel='Count'>
```



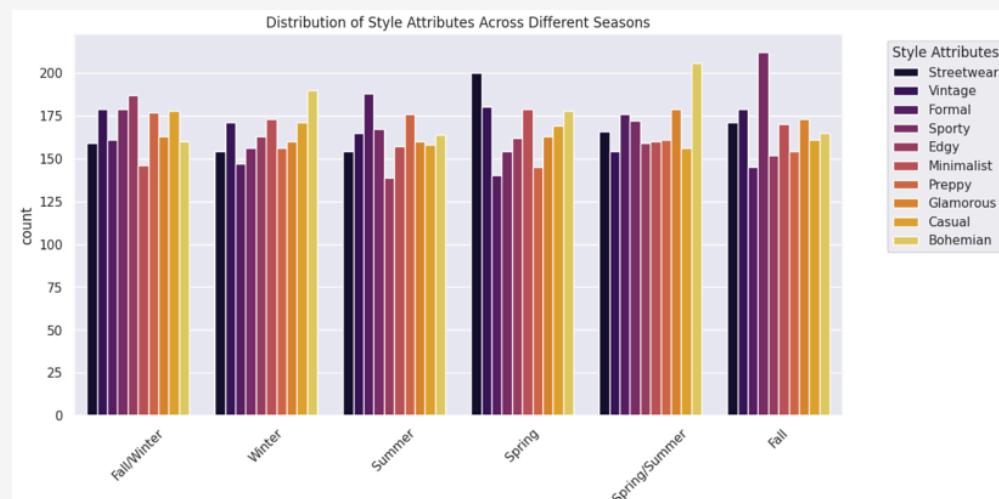
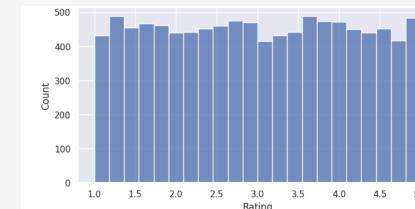
DEMAND FOR  
ALL  
PRICEPOINTS  
OF PRODUCTS.



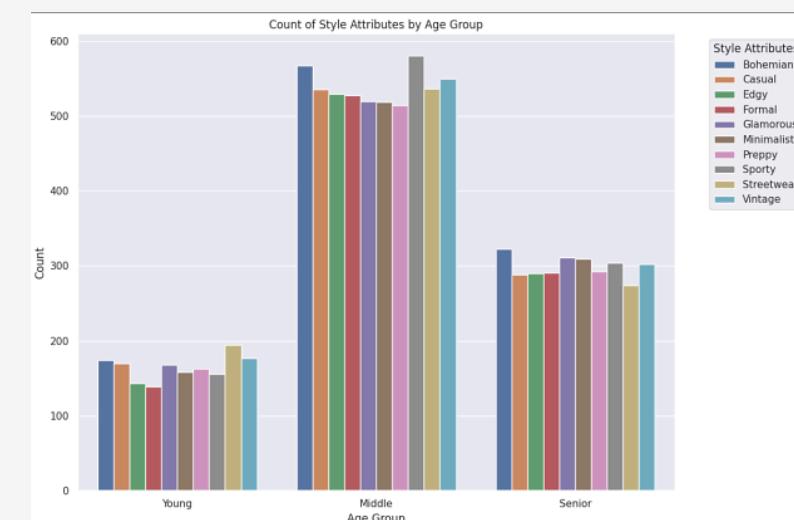
```
#visualization for rating  
f, axes = plt.subplots(1, 2, figsize=(18, 4))  
sb.boxplot(data = salesdata['Rating'], orient = "h", ax = axes[0])  
sb.histplot(data = salesdata['Rating'], ax = axes[1])  
  
<Axes: xlabel='Rating', ylabel='Count'>
```



RATINGS  
ARE ALSO  
FAIR



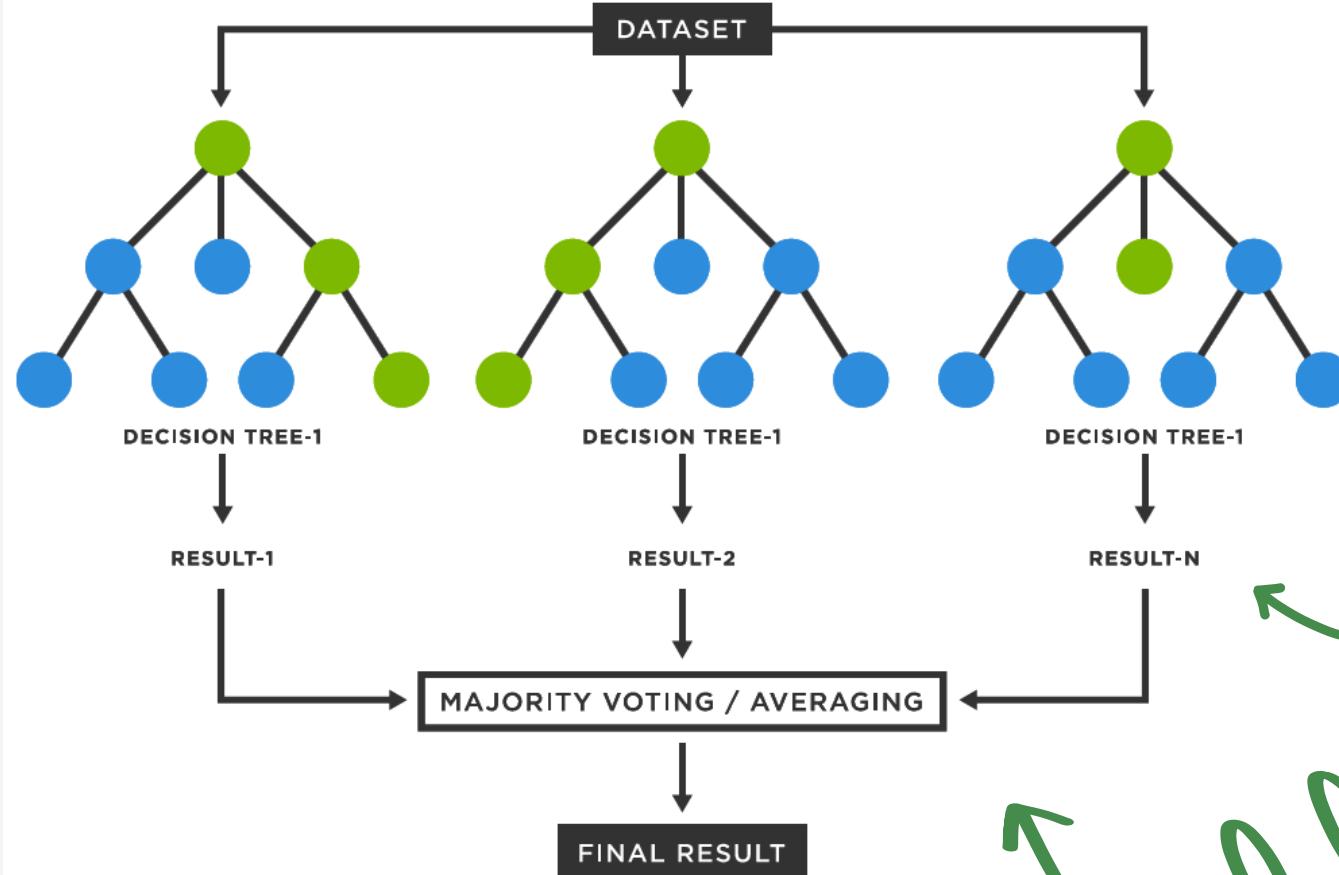
WITHIN  
SEASON



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

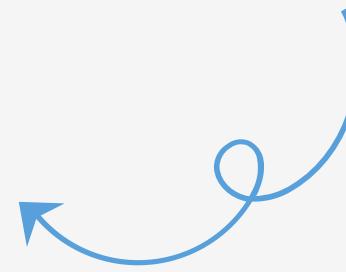
AGE-SPECIFIC VARIATIONS  
MIGHT NOT BE SUFFICIENTLY  
CAPTURED BY THE MODEL

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

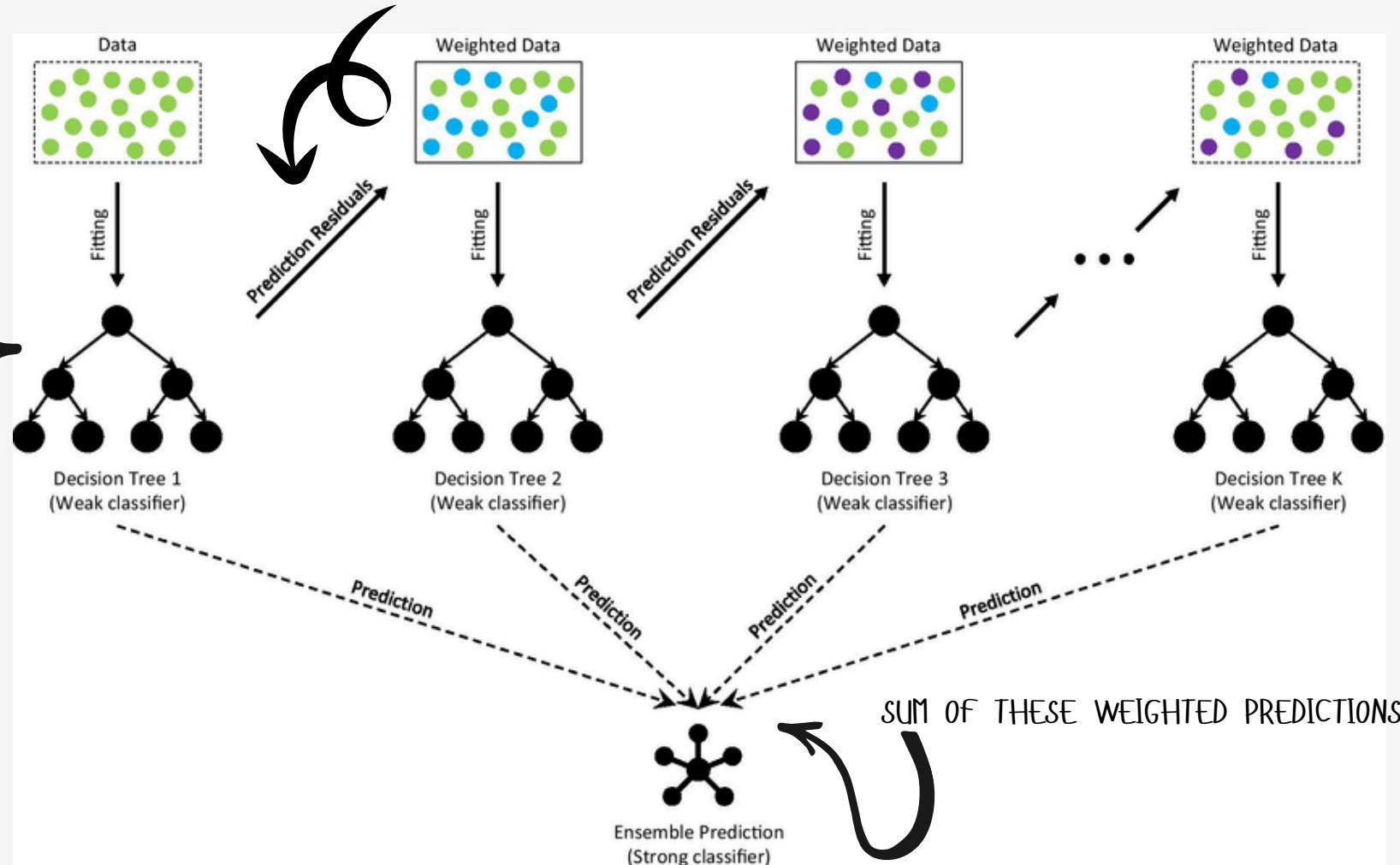
accuracy for Season-Based Split: 8.57%

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

## GRADIENT BOOSTER

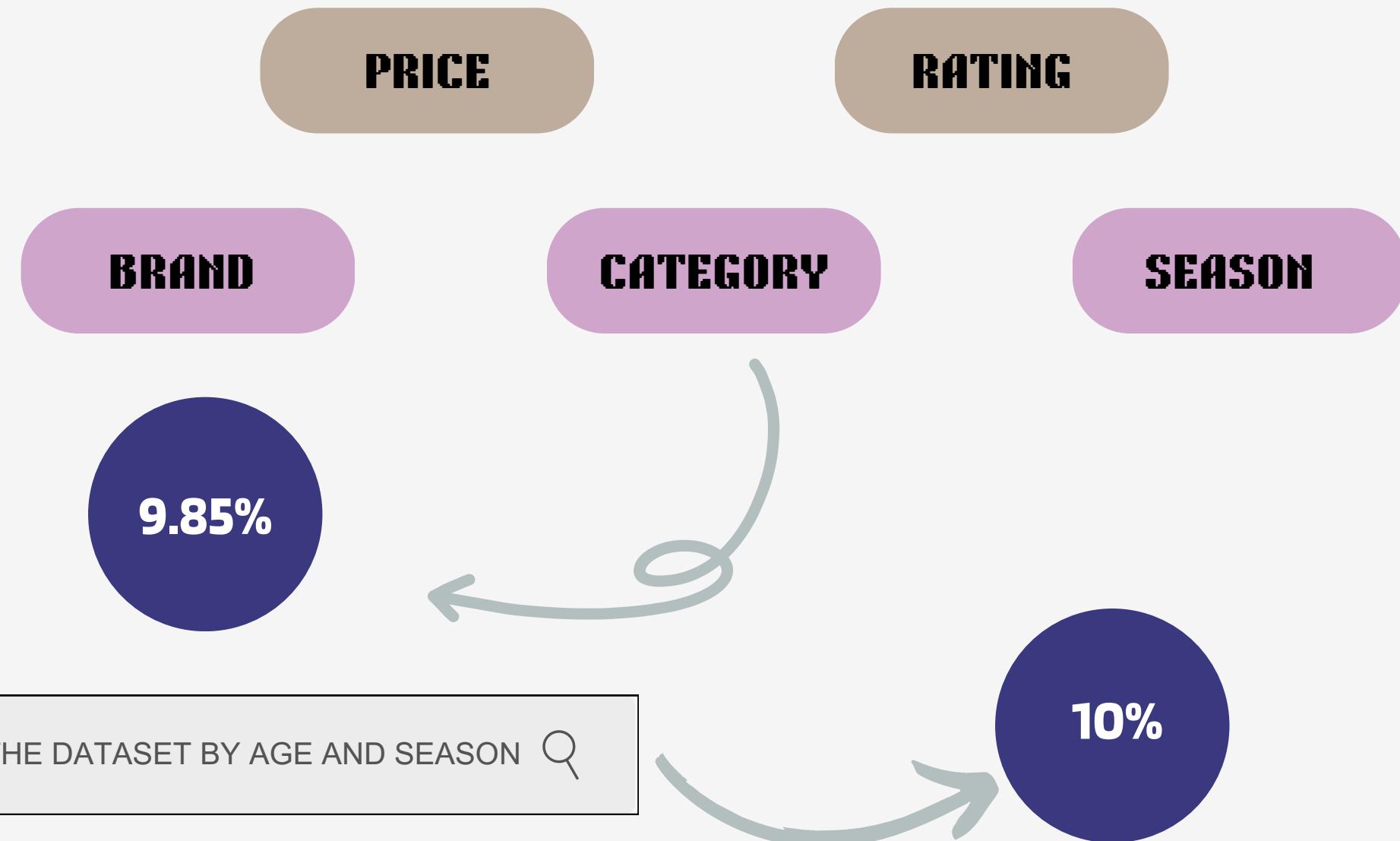
SUBSEQUENT MODELS FOCUS ON CORRECTING THESE  
ERRORS BY PREDICTING THE RESIDUALS

CALCULATES THE  
ERRORS (RESIDUALS)



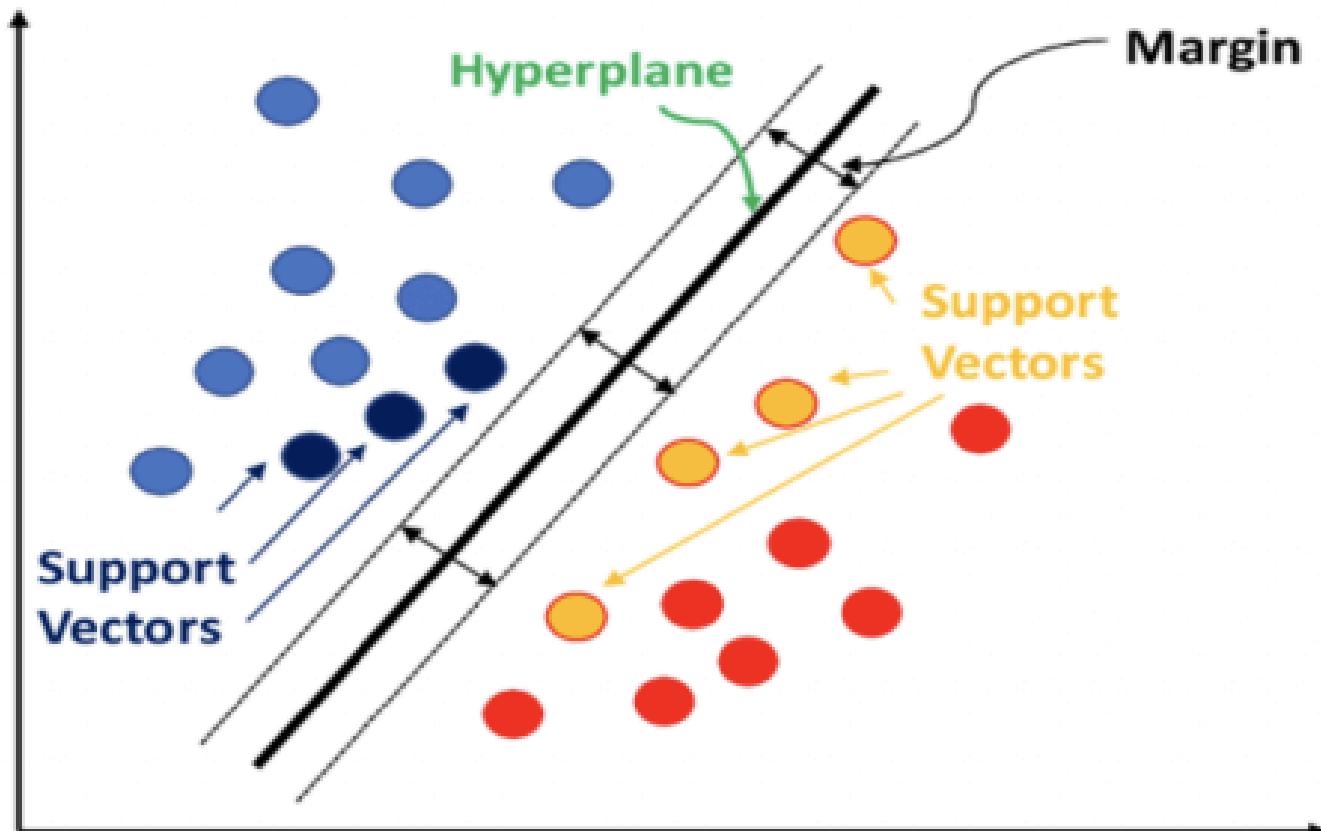


# FASHION PREDICTION

[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



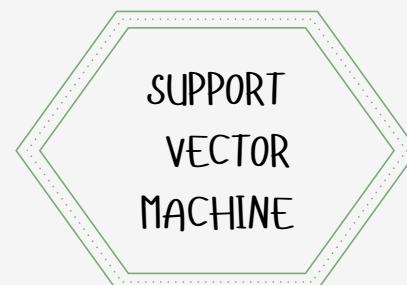
9.85%

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!!

