Boyota Customer Promotion plan

METIS BOOTCAMP

PLAN

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Boyota.CORP
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Contents

CONTENTS

01.**Background introduction**

02. **Methodo -logy**

03. **Data Explan -ation & EDA**

04. **ML Models comparison**

05. **Deeper explore**

06.**Further Steps**

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Background Introduction

Business Problems Raised

- Boyota Corp. is a Japanese automobile company has plans to enter US markets with their existing products (P1, P2, P3, P4 and P5)
- Sales team has classified all customers into **A,B,C,D** class, they plan to use the same strategy on new markets and have identified 2627 new potential customers.
- We are required to help the manager to predict the right group of the new customers.

Methodology

Solution Path

Modeling Goal

Find Common/Different Characteristics of Customers:

- Gender
- Age
- Graduation
- Family Size
- Profession
- Marriage

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ML Method

Find Suitable Machine Learning Methods

- KNN
- Random Forest
- Decision Tree
- Naïve Bayes

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Business Goal

Correctly Assign Potential Customers to Their Segments

Achieving Successful Customer Management

↓

Maximize profits

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Data Explanation & EDA

Features Explanation

Variable	Definition
ID	Unique ID
Gender	Gender of the customer
Ever_Married	Marital status of the customer
Age	Age of the customer
Graduated	Is the customer a graduate
Profession	Profession of the customer
Work_Experience	Work Experience in years
Spending_Score	Spending score of the customer
Family_Size	Number of family members for the customer (including the customer)
Var_1	Anonymised Category for the customer
Segmentation	(target) Customer Segment of the customer

We will show some important Features:

- Work experience
- Spending Score
- Age
- Marriage
- Family Size

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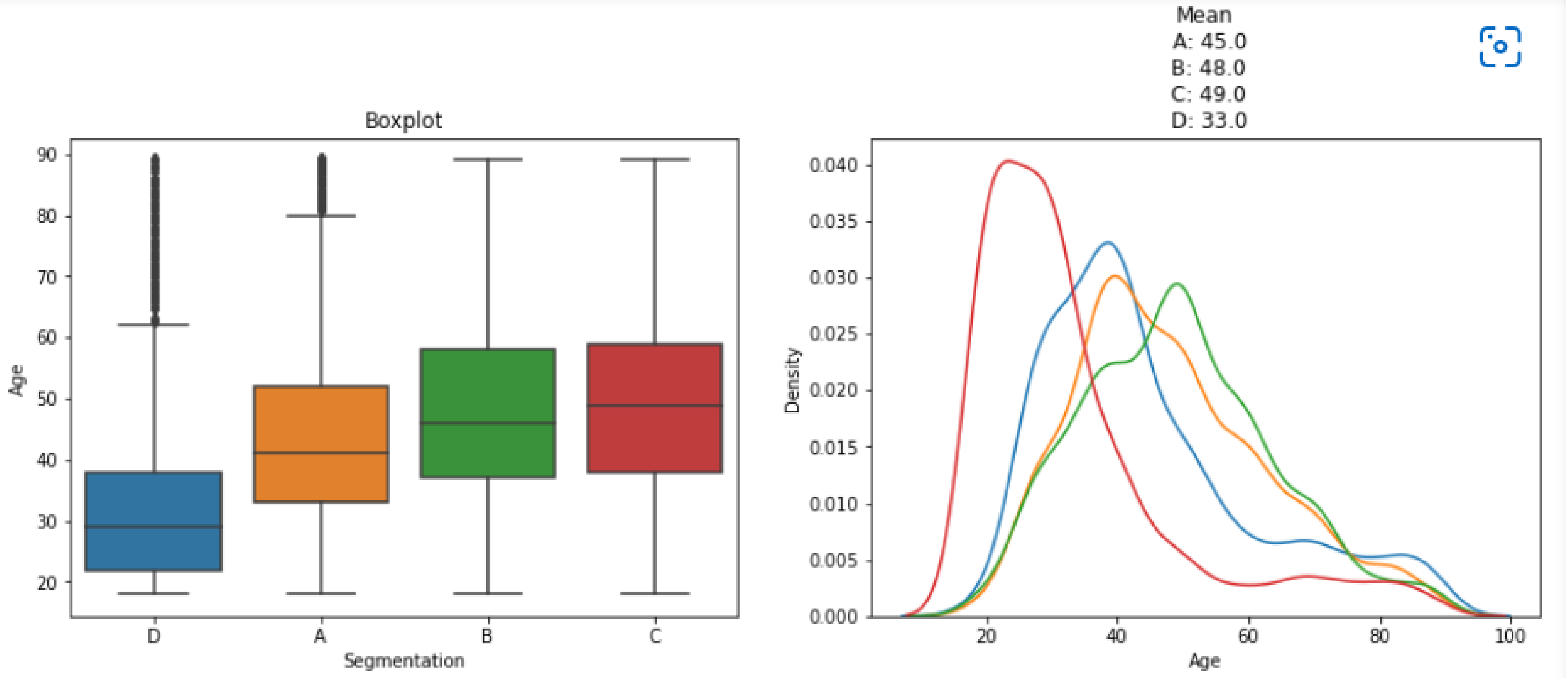
Exploratory Data Analysis-Important detection

Age

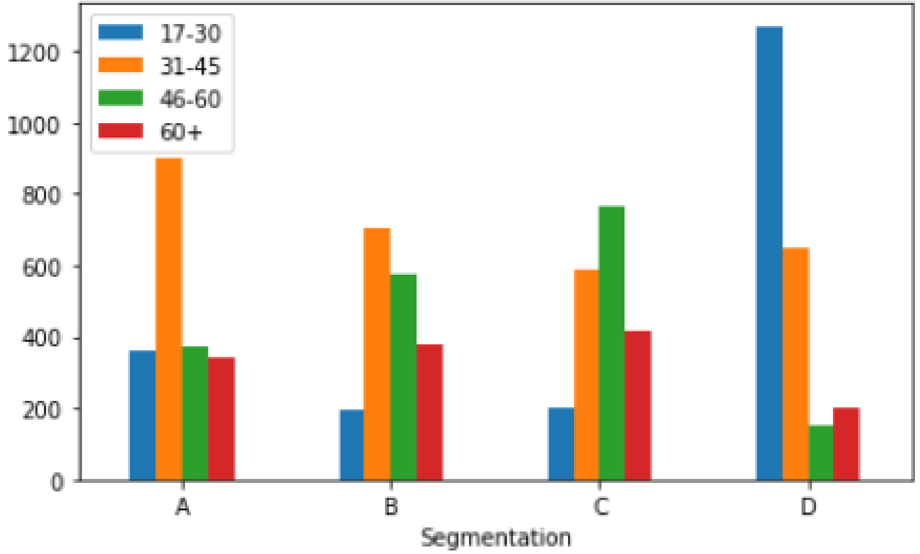


D: youngest C: oldest, D<A<B<C

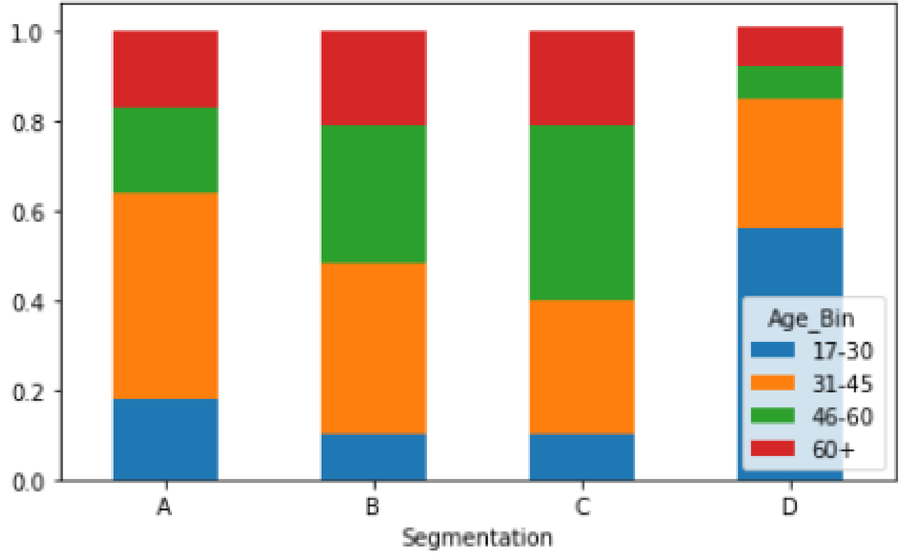
Exploratory Data Analysis-Important detection

Age-bin(17-30, 31-45,46-60,60+)

Segmentation	17-30	31-45	46-60	60+
A	360	898	373	341
B	195	707	575	381
C	201	588	767	414
D	1270	647	150	201



Age_Bin Segmentation	17-30	31-45	46-60	60+
A	0.18	0.46	0.19	0.17
B	0.10	0.38	0.31	0.21
C	0.10	0.30	0.39	0.21
D	0.56	0.29	0.07	0.09



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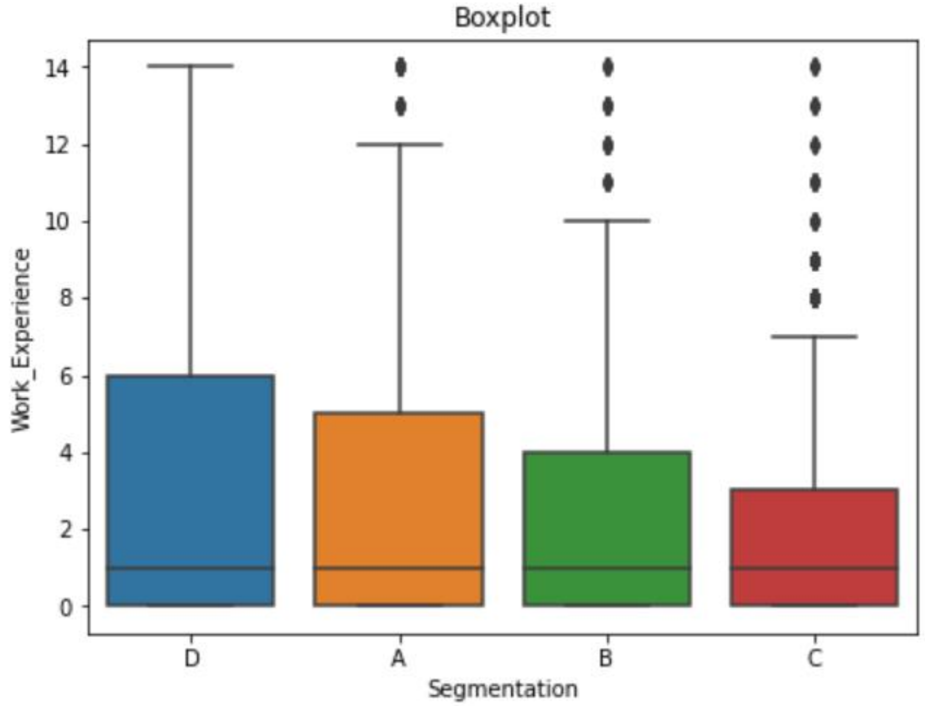
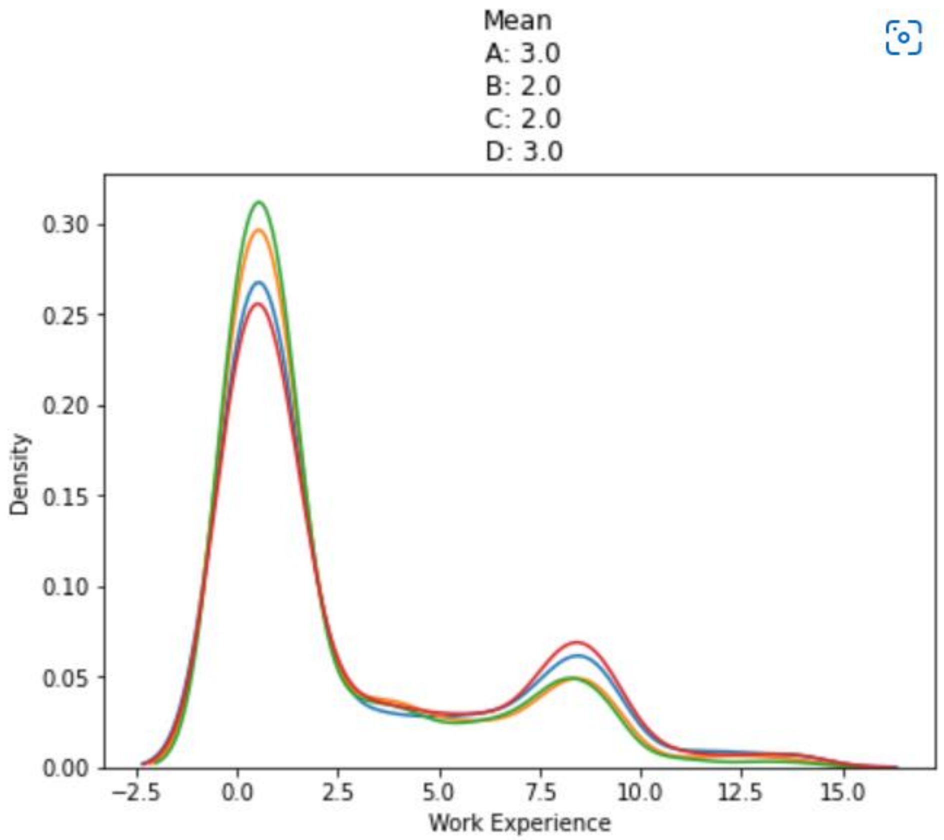
Exploratory Data Analysis-Important detection

Work Experience



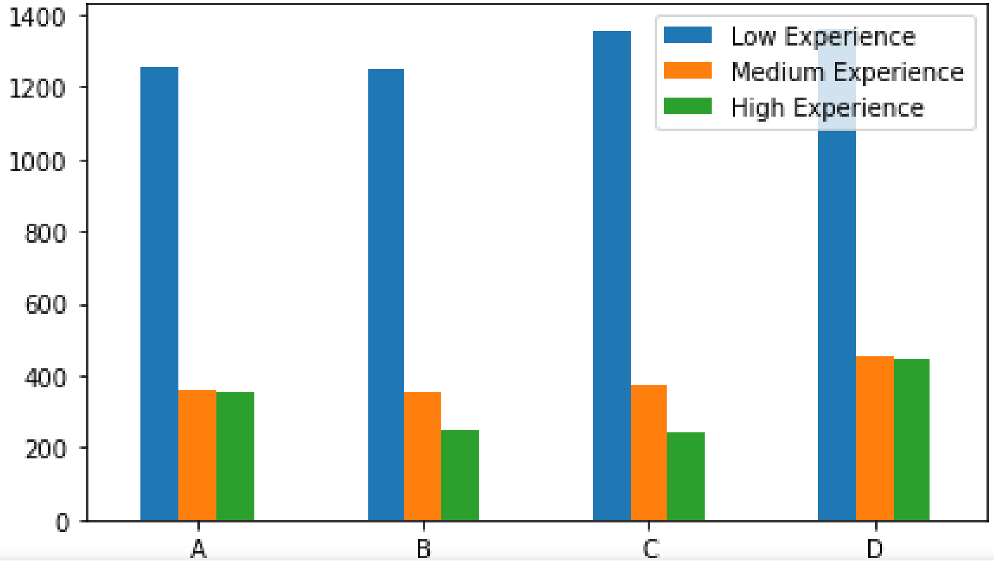


D: highest C: lowest, D>A>B>C

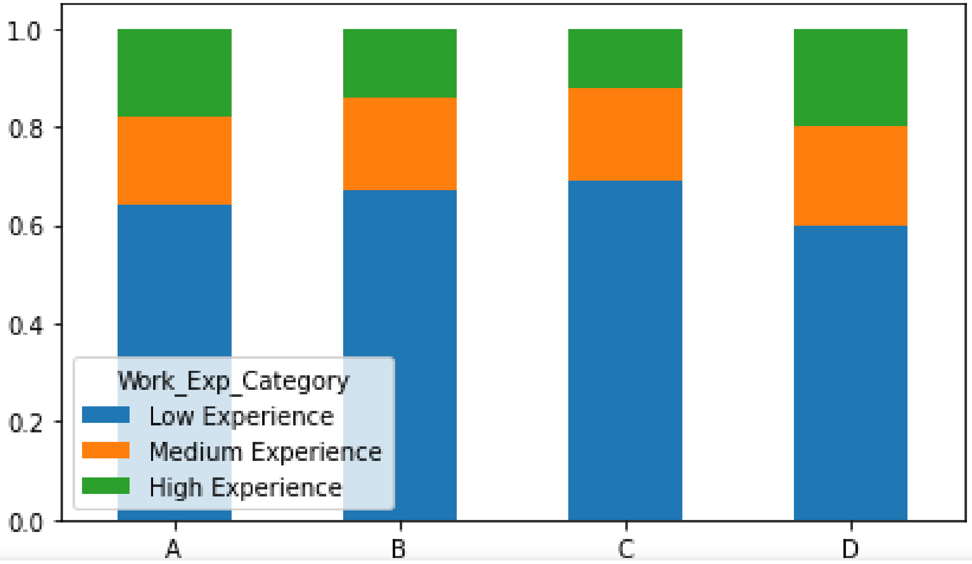
Exploratory Data Analysis-Important detection

Work Experience-bin(0-1,1-7,7-15)

Segmentation	Low Experience	Medium Experience	High Experience
A	1257	358	357
B	1252	354	252
C	1354	375	241
D	1363	456	449



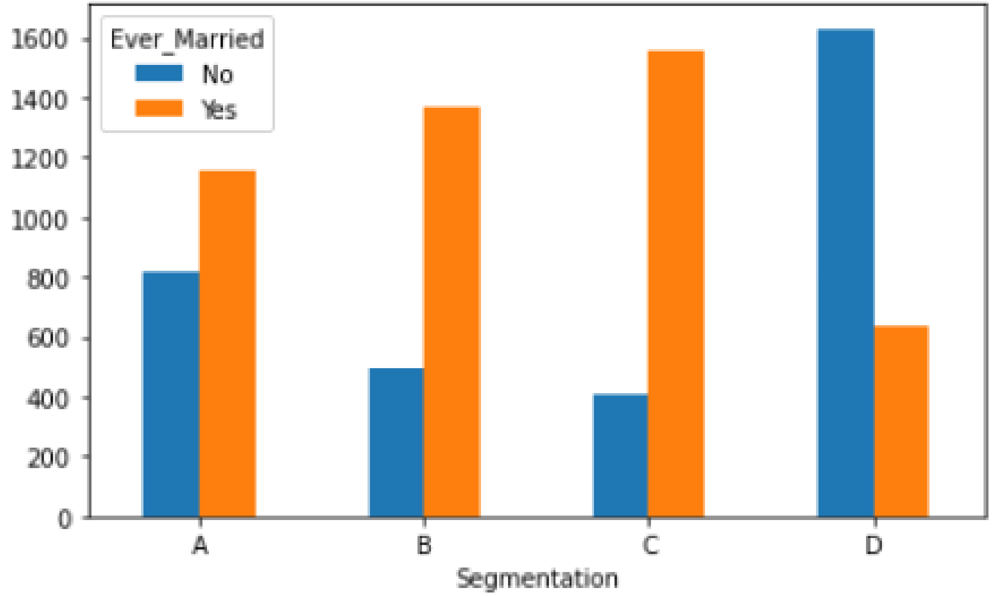
Work_Exp_Category Segmentation	Low Experience	Medium Experience	High Experience
A	0.64	0.18	0.18
B	0.67	0.19	0.14
C	0.69	0.19	0.12
D	0.60	0.20	0.20



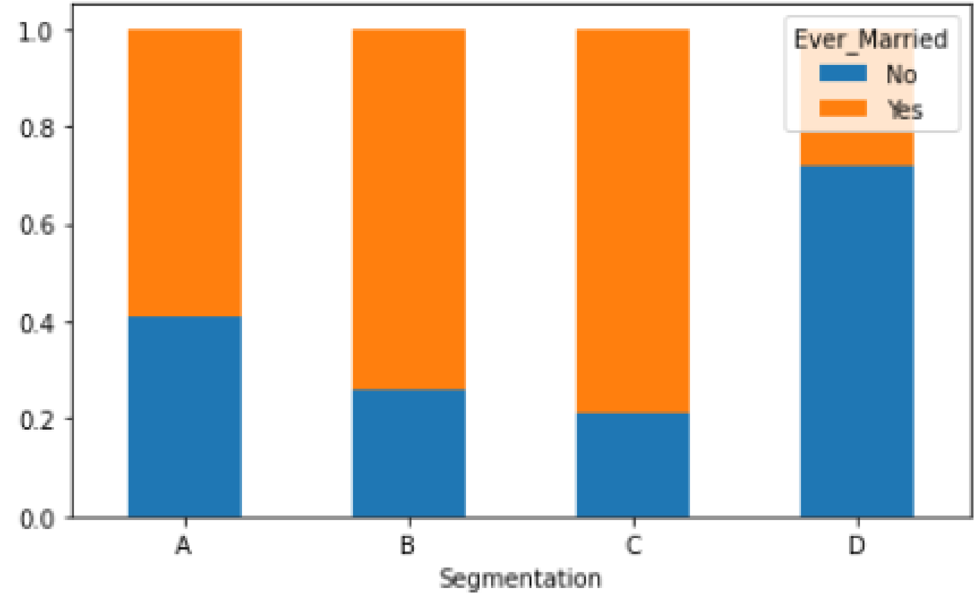
Exploratory Data Analysis-Important detection

Marriage

Ever_Married	No	Yes
Segmentation		
A	816	1156
B	491	1367
C	410	1560
D	1631	637



Ever_Married	No	Yes
Segmentation		
A	0.41	0.59
B	0.26	0.74
C	0.21	0.79
D	0.72	0.28

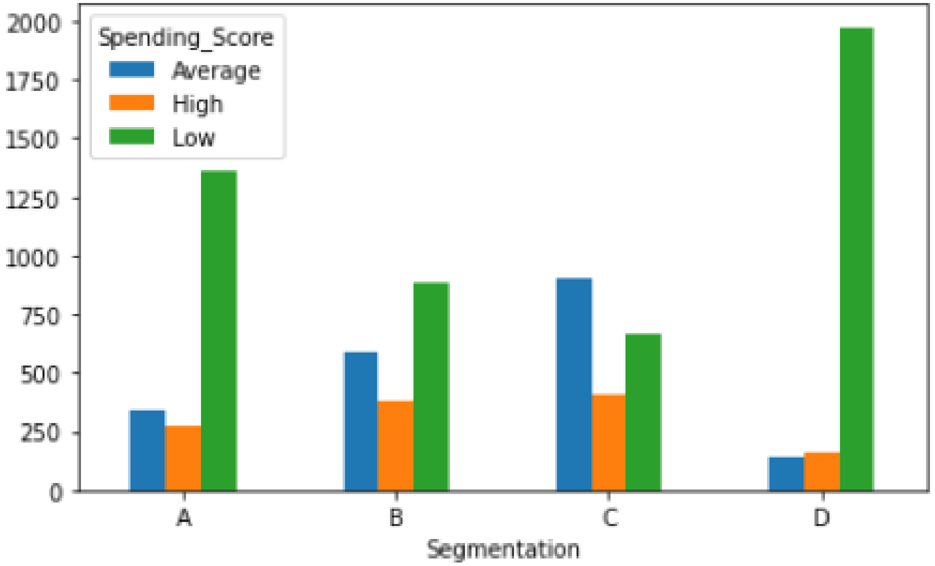


D: Most unmarried C: Most Married

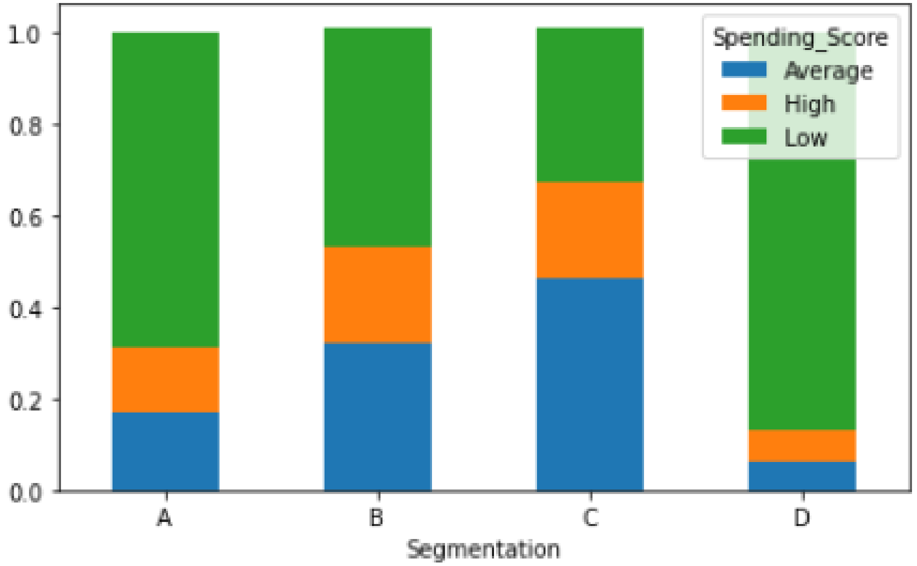
Exploratory Data Analysis-Important detection

Spending Score

Spending_Score Segmentation	Average	High	Low
A	343	271	1358
B	590	384	884
C	903	405	662
D	138	156	1974



Spending_Score Segmentation	Average	High	Low
A	0.17	0.14	0.69
B	0.32	0.21	0.48
C	0.46	0.21	0.34
D	0.06	0.07	0.87



D: Most Low Spending Score C: Least Spending Score

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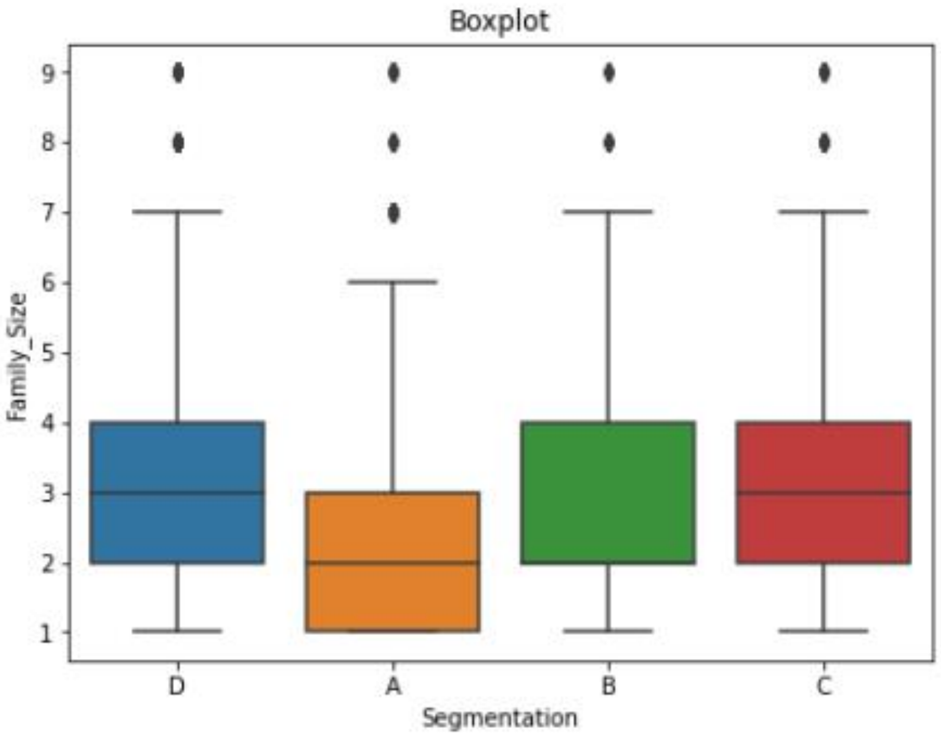
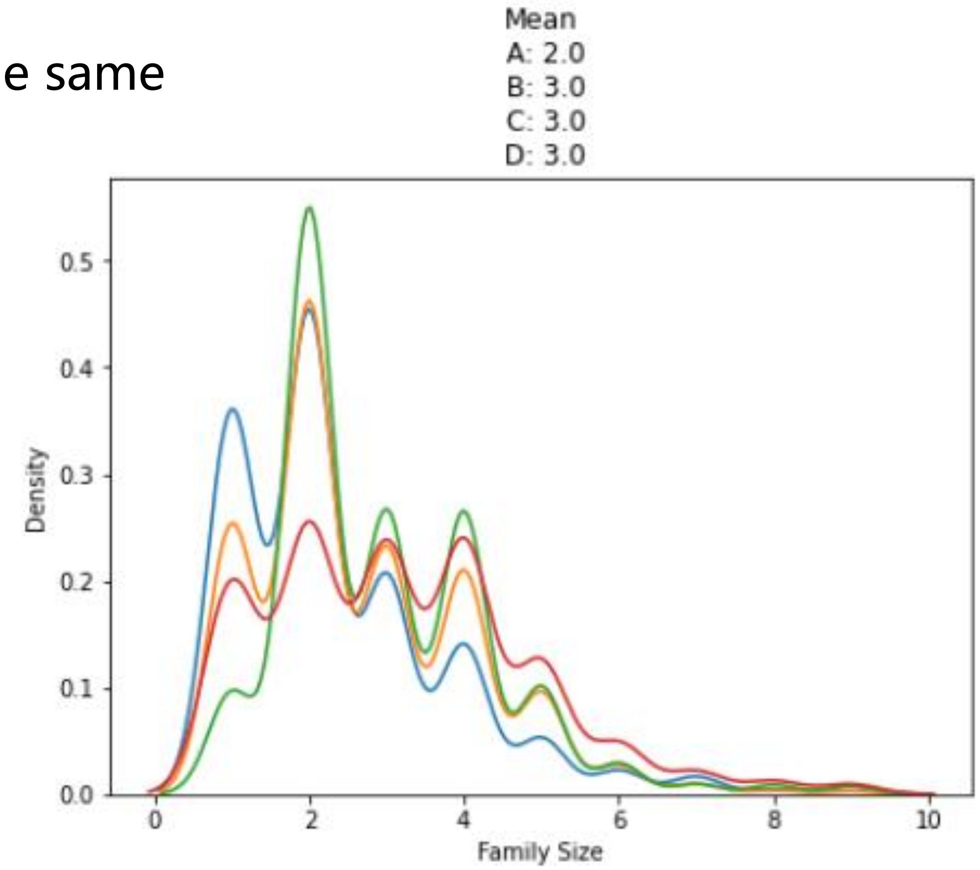
Exploratory Data Analysis-Important detection

Family Size

A: smallest Family size, Others about the same





Exploratory Data Analysis-Important detection

Conclusion

- Segment C (sketch: student/entry-level employees)
  - highest average age
  - married
  - lowest working experience
  - higher than other segments 'spending score
- Segment D (sketch: middle-aged wealthy customers)
  - lowest average age
  - unmarried
  - highest working experience
  - lower than other segments 'spending score
- Segment A has the smallest family size
- Hard to tell segments B from features

ML Models comparison

ML methods comparison

ML Methods	F1 Scores(Train)	F1 Scores(Test)
K-nearest neighbors(Normalized)	0.69	0.41
K-nearest neighbors(Dummy variables)	0.60	0.45
Random Forest(Normalized)	0.96	0.46
Random Forest(Dummy variables)	**0.72**	**0.47**
Naïve Bayes(Normalized)	0.48	0.47
Naïve Bayes(Dummy variables)	0.50	0.49

* I deleted dummy method of KNN and all Naïve Bayes method to simplify my Notebook

ML Models comparison

Final Choice of ML Methods

- Final Choice: Random Forest
  - Flexible, higher F1 scores
- Random Forest(Normalized)
  - Train data overfitting
- K-nearest neighbors
  -Both of F1 scores are lower than random forest.
  -In normalized dataset, KNN has a good performance may because that the original Dataset is built on K-means
- Naïve Bayes
  - Assumption not suitable

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Deeper explore

Segment B distinguish

	A	B	C	D
A	235	**148**	69	140
B	**155**	160	**153**	89
C	66	**145**	286	94
D	144	56	26	455

*Confusion Matrix of RF(Dummy method)

- 155 B are considered as A
- 148 A are considered as B
- 145 C are considered as B
- 153 B are considered as C
- B has the least obvious features as seen in EDA

Deeper explore

Segment B distinguish

	F1 Score(Train)	F1 Score(Test)
B	0.56	0.24
Not B	**0.91**	**0.85**

*Random Forest Methods For B/Not B Test

- Still hard to tell Segment B
- Easier to tell Segment which is not B

Conclusion

Conclusion& Inspiration

- From the EDA& Confusion Matrix:
  - Segment B is the hardest part to tell
  - Segment C & D have clearer customer sketches

- Reason for choosing Random Forest:
  - Flexibility
  - Ability to deal with noise
  - Ability to deal with more features
  - Nice F1 Score (and precision score)

- New models to tell not segment B groups

- Accuracy is low no matter what we choose

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Further Steps

Further Steps to Impel Project

ID Features Explore

ID seems have some information to tell but we directly drop it

Web App

Build a web app by flask for better visualization and communication

Boyota CORP.

Thank You

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