Technical Appendix

Polo SKU Productivity Modelling

Introduction

The purpose of this project was to determine the key attributes that influence SKU productivity. To do this, we developed a classification modeling system to measure the marginal impact that individual levels within a given attribute (i.e., red is a level in the attribute super color) have on the overall predicted probability of productivity.

To achieve this, we iterated through numerous different forms of classification modeling to find a balance between interpretability and accuracy, ending on a Random Forest model for men's tops, men's bottoms, women's tops, and women's bottoms. An XG-Boost model was used for outerwear as its performance was higher. These models were chosen due to their ability to effectively deal with categorical and binary variables of which the dataset included much of.

The following appendix will begin by detailing the specific attributes and levels included in each model and give a brief explanation of the data cleaning and preparation process. It will then include key metrics and graphs related to model performance giving an overview of the effectiveness of each model. Finally, we will outline the most impactful levels within each model for making predictions and present partial dependence plots depicting how each level within the most important attributes affects the probability of productivity on average.

Data Preparation Process

As the initial data was already relatively clean and complete, there was not a significant amount of work involved in this process. Due to the number of categorical variables containing a large number of levels, time was spent combing through each attribute individually to ensure only levels with a significant number of products attached were used within the model. For example, under fiber content for men's tops, leather contained only 1 product while cotton contained 8010. To not impact the performance of the model, levels such as leather were removed. In addition, string detection was utilized to parse thought variables with thousands of unique levels such as march fabrication to group them into more usable levels such as "Oxford", "Denim" or "Terry". Finally, a binary variable to check for productivity was created that was assigned 1 if a products global SKU score was a 1,2,3 or 4 and 0 if it wasn't.

This data cleaning process took place for 5 distinct categories including Mens tops, Mens bottoms, Women's tops, Women's bottoms, and Mens Outerwear to account for differences in important attributes within different product categories (i.e., neckline for tops vs length for pants).

Target Exploration

If we have anything for here

Men Tops

Used Variables

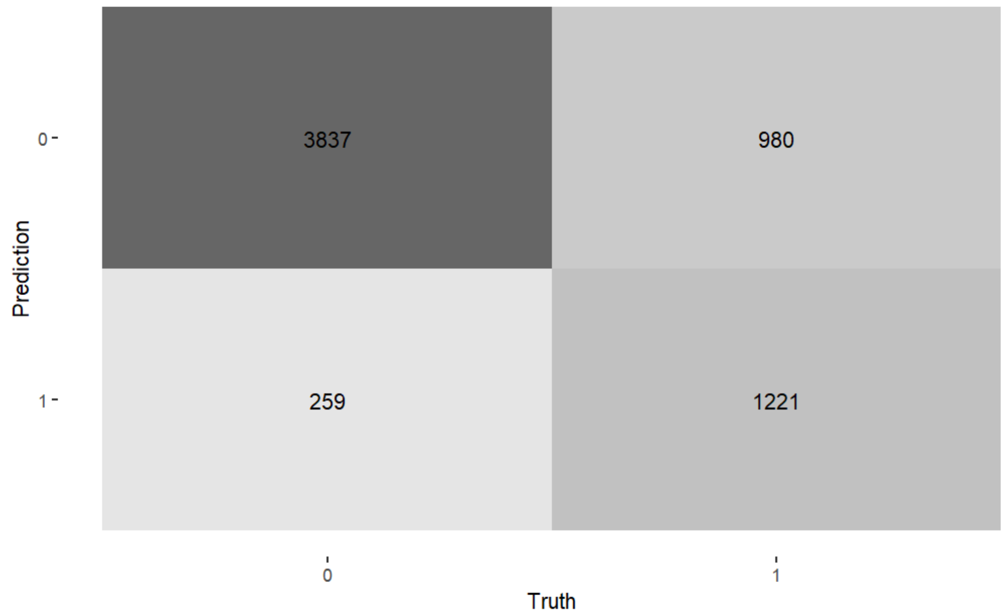
- **Fashion Degree:** seasonal, seasonal core, core
- **Fiber Content:** cotton linen, nylon, polyester, silk, wool, cashmere
- **Global Plan L4:** polo shirt, sport shirts, sweat shirt, sweaters, t-shirts, knits
- **Logo:** branded, label, monogram, no logo, other branding, polo bear, polo sport, small player, rl embroidery
- **Material Group:** sweaters, wovens, knits
- **Neckline:** collar, crew neck, hoodie, mock neck, not applicable, other, polo knit collar, polo self-collar, spread collar, turtleneck, v neck, button down collar
- **Pricing:** good, better, best, luxury
- **Style Pattern:** stripe, solid, print, plaid/check, novelty, heather/mélange
- **Merch Fabrication:** jersey, mesh, interlock, twill, fleece, oxford, cotton, dbl knit, denim, terry, poplin, wool, seersucker, cashmere, linen, corduroy, nylon, chambray
- **Super Color**

Final Model

Random Forest, trees = 1599, min_n = 2

Training Set Metrics & Confusion Matrix:

.metric <chr>	.estimator <chr>	.estimate <dbl>
accuracy	binary	0.8032396
kap	binary	0.5318145
mn_log_loss	binary	0.4467290
roc_auc	binary	0.8924504



Testing Set Metrics & Confusion Matrix:

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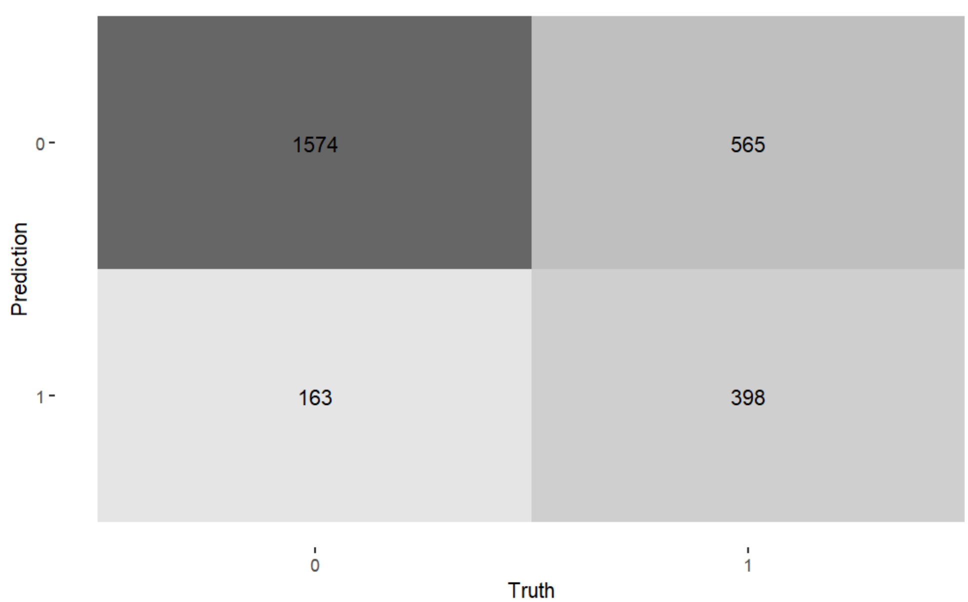
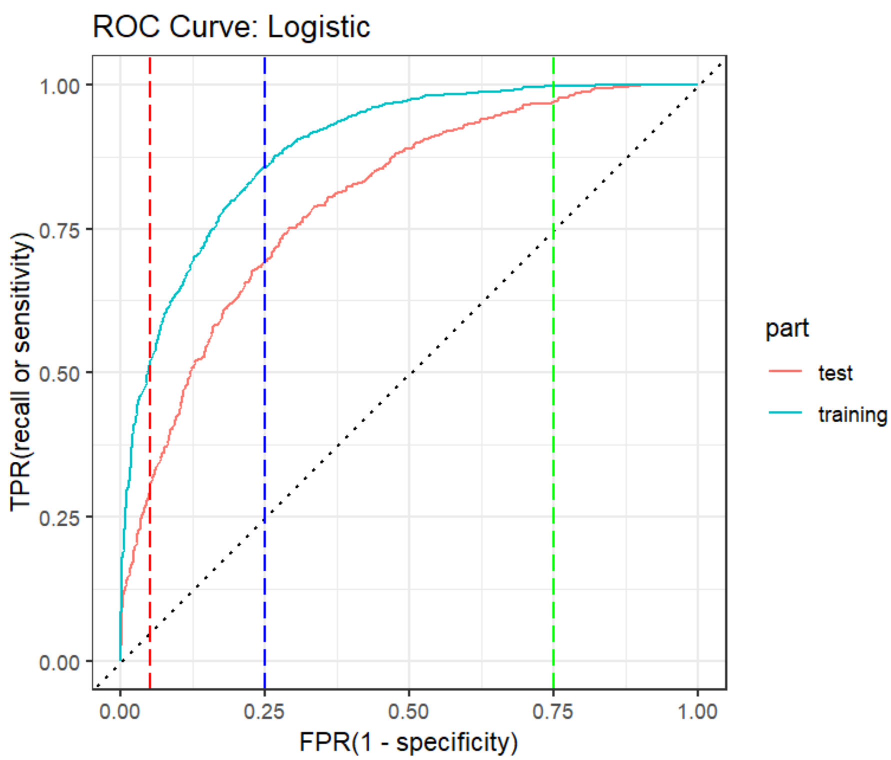
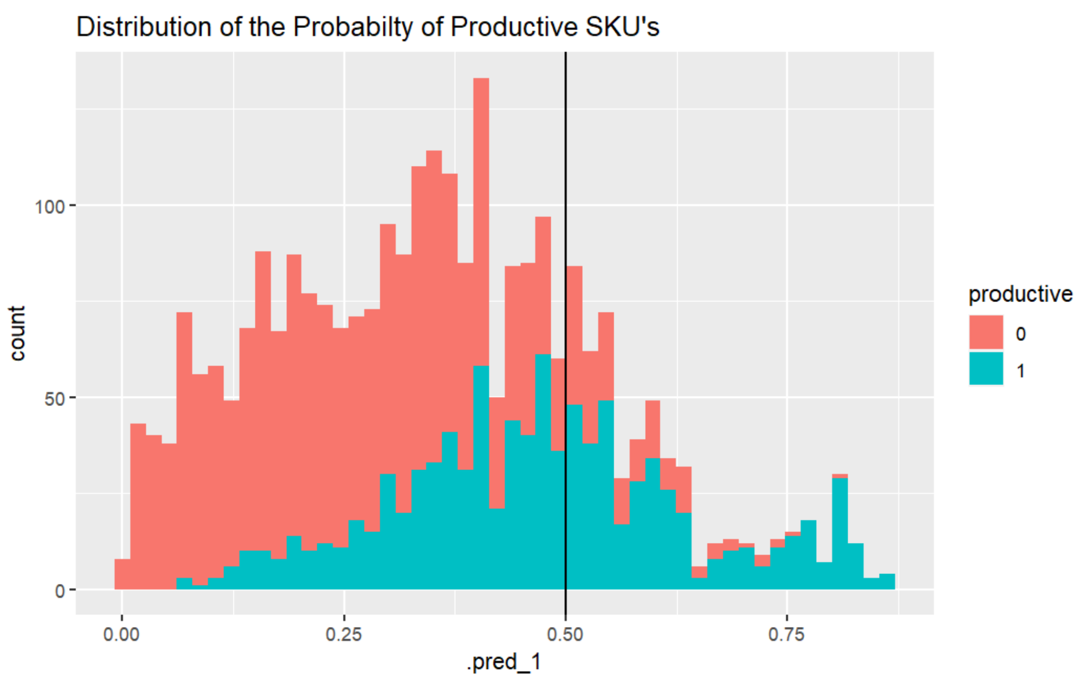
kap	binary	0.3522094
mn_log_loss	binary	0.5202201
roc_auc	binary	0.8000195



ROC Curve (False Positive Rate on X Axis, True Positive Rate on Y Axis):

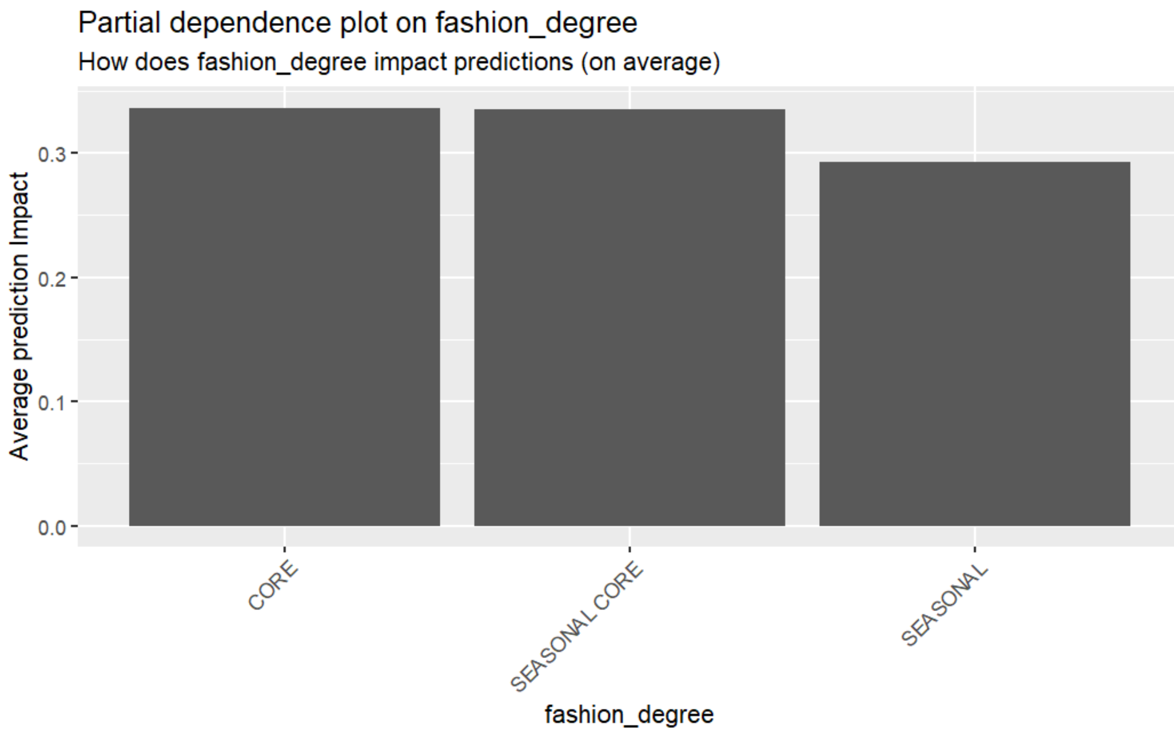


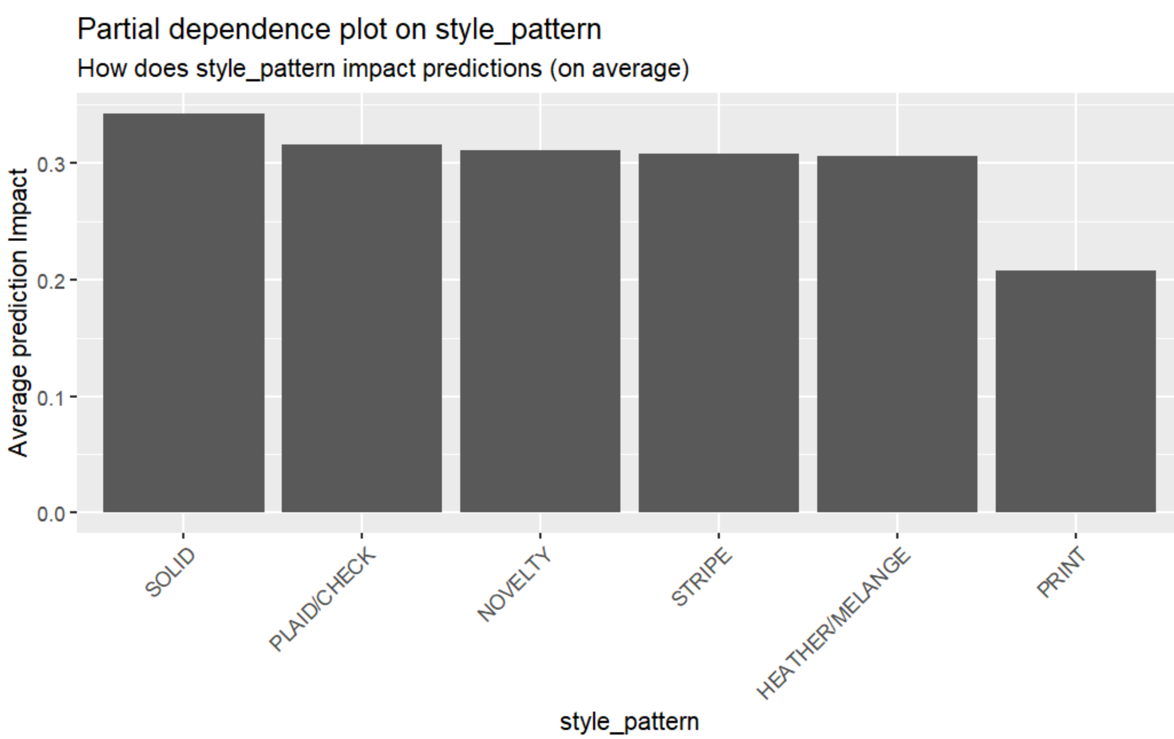
Distribution of Productive Probabilities:

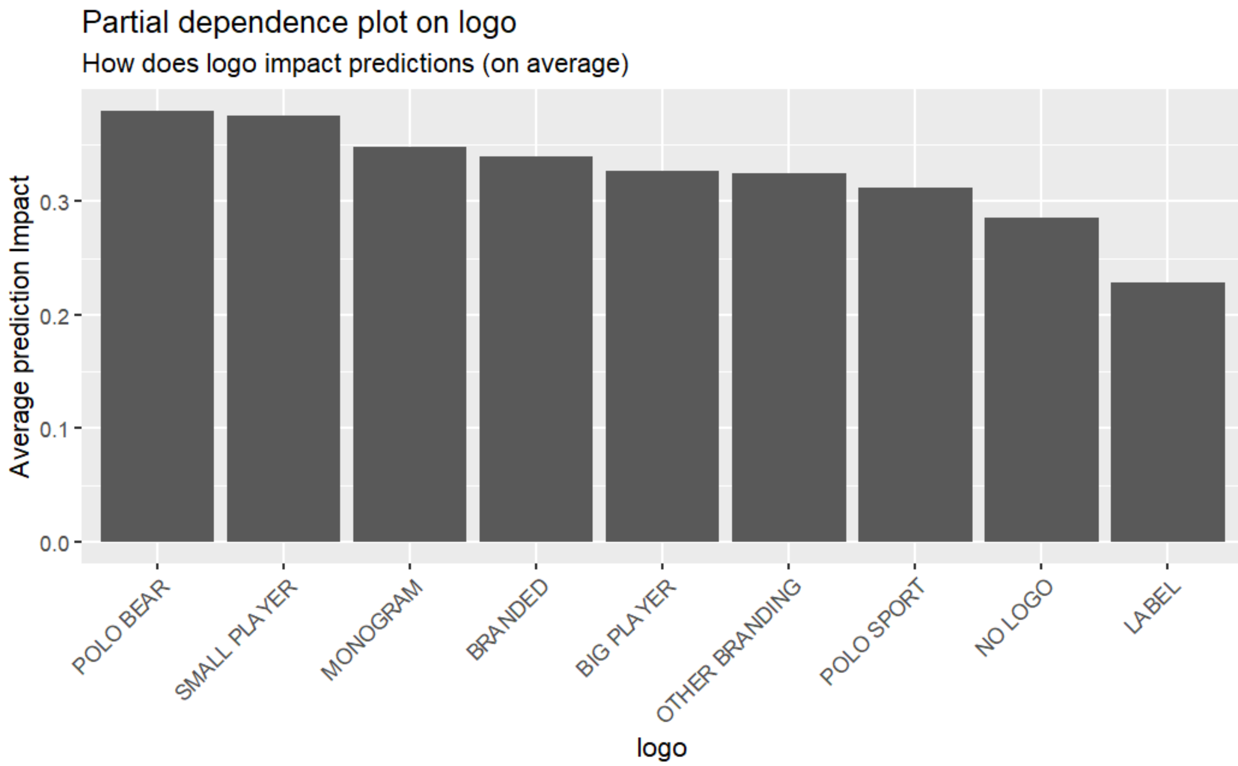


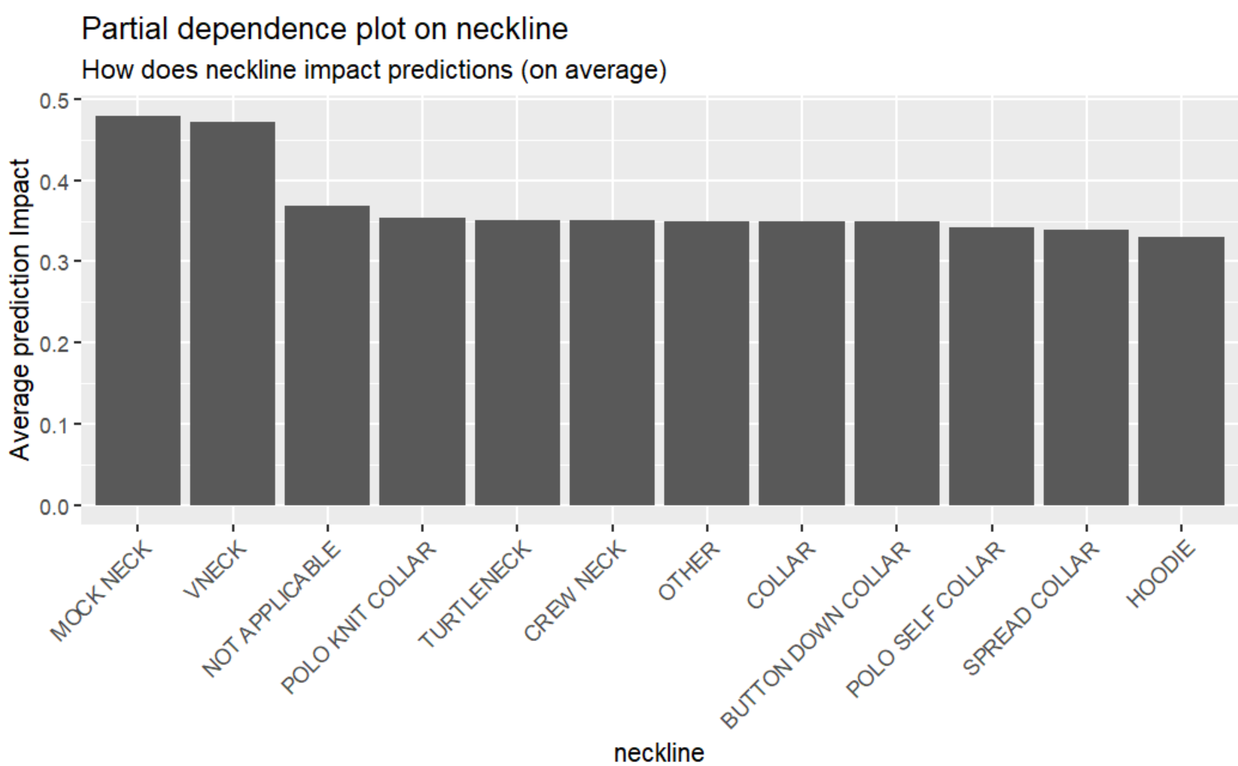
- pred_1 is the probability of productivity while the fill indicates the score of the product (1 for productive, 0 for unproductive)

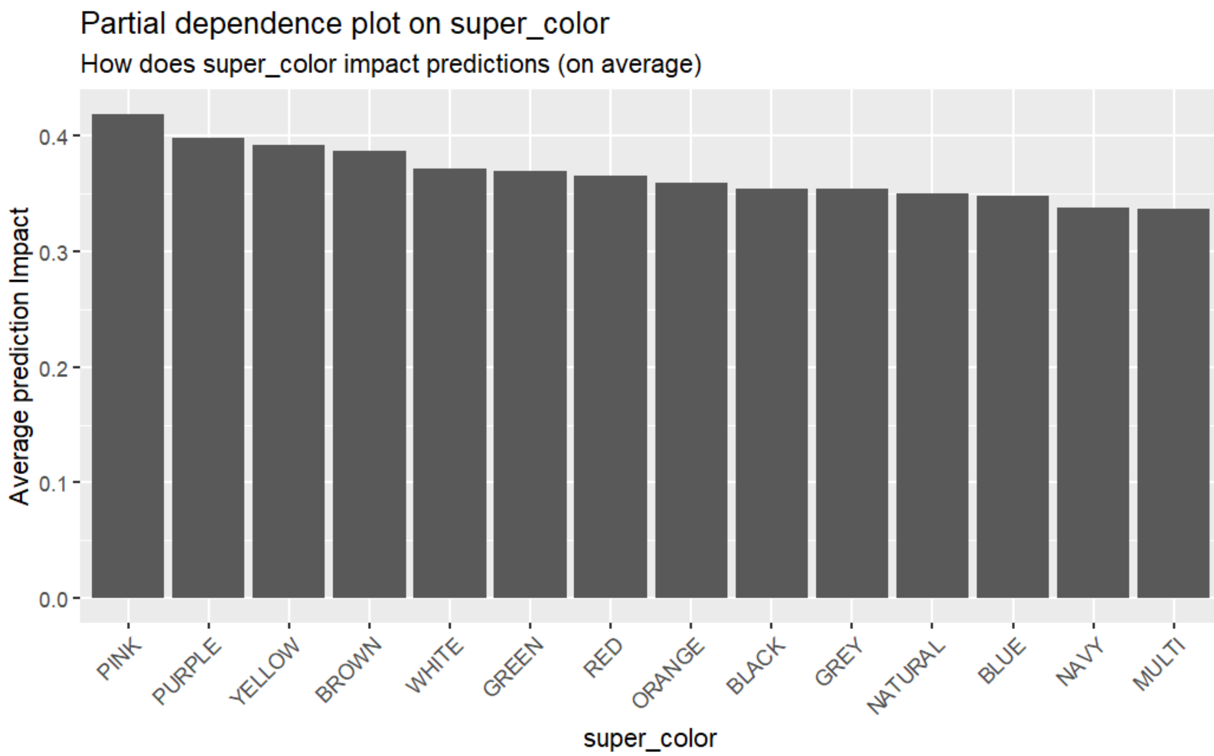
Partial Dependency Plots:

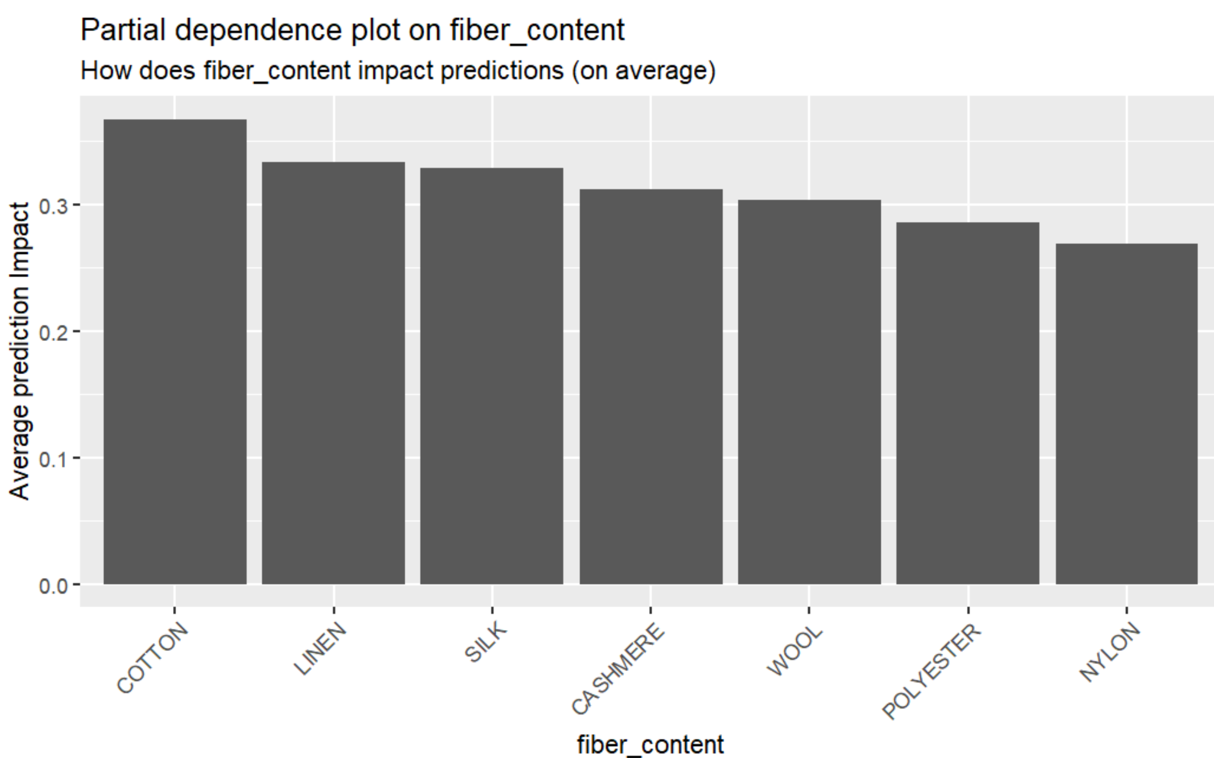





Partial dependence plot on logo
How does logo impact predictions (on average)
Average prediction Impact
0.0
0.1
0.2
0.3
POLO BEAR
SMALL PLAYER
MONOGRAM
BRANDED
BIG PLAYER
OTHER BRANDING
POLO SPORT
NO LOGO
LABEL
logo


Partial dependence plot on neckline
How does neckline impact predictions (on average)
Average prediction Impact
0.0
0.1
0.2
0.3
0.4
0.5
MOCK NECK
VNECK
NOT APPLICABLE
POLO KNIT COLLAR
TURTLENECK
CREW NECK
OTHER
COLLAR
BUTTON DOWN COLLAR
POLO SELF COLLAR
SPREAD COLLAR
HOODIE
neckline


Partial dependence plot on super_color
How does super_color impact predictions (on average)
Average prediction Impact
0.0
0.1
0.2
0.3
0.4
PINK
PURPLE
YELLOW
BROWN
WHITE
GREEN
RED
ORANGE
BLACK
GREY
NATURAL
BLUE
NAVY
MULTI
super_color


Partial dependence plot on fiber_content
How does fiber_content impact predictions (on average)
Average prediction Impact
0.0
0.1
0.2
0.3
COTTON
LINEN
SILK
CASHMERE
WOOL
POLYESTER
NYLON
fiber_content

The above plots show the average probability of productivity of a specific level within an attribute, holding all else constant. For example, looking at super color we can see that on average, **purple** men's tops have a 40% probability of having a global SKU productivity score of 1, 2, 3 or 4 according to the model. When compared to **blue** men's tops which on average have a 35% probability of being productive, we can conclude that purple men's tops have a 5% higher probability of being productive than blue tops on average. It is important to remember that this is an aggregation. There will be numerous purple tops that are not productive as well as numerous blue tops which are, this method simply looks at the score assigned to each product within a category holding every other attribute (fiber content, fashion degree etc.) constant and takes an average of that score. It is incredibly useful for decoding more complex "black box" machine learning methods such as the random forest model.

Men Bottoms

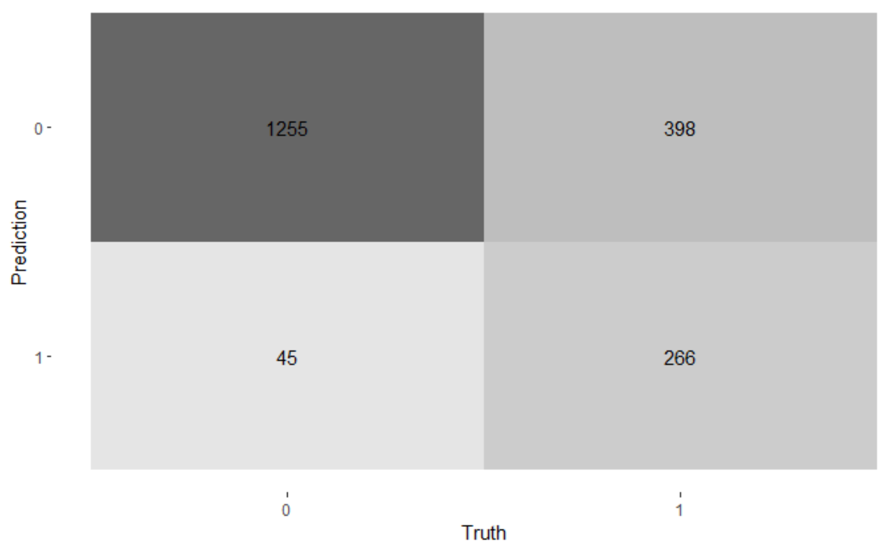
Used Variables

- **Fashion Degree:** seasonal, seasonal core, core
- **Fiber Content:** cotton, linen, polyester
- **Global Plan L4:** pants, jeans, trousers, shorts
- **Logo:** big player, branded, label, monogram, no logo, polo sport, rl (embroidery), small player
- **Pricing:** good, better, best, luxury
- **Style Pattern:** stripe, solid, print, novelty, mixed media
- **Super Color**

Final Model

Random Forest trees=80, min_n=15

Training Set Metrics & Confusion Matrix:

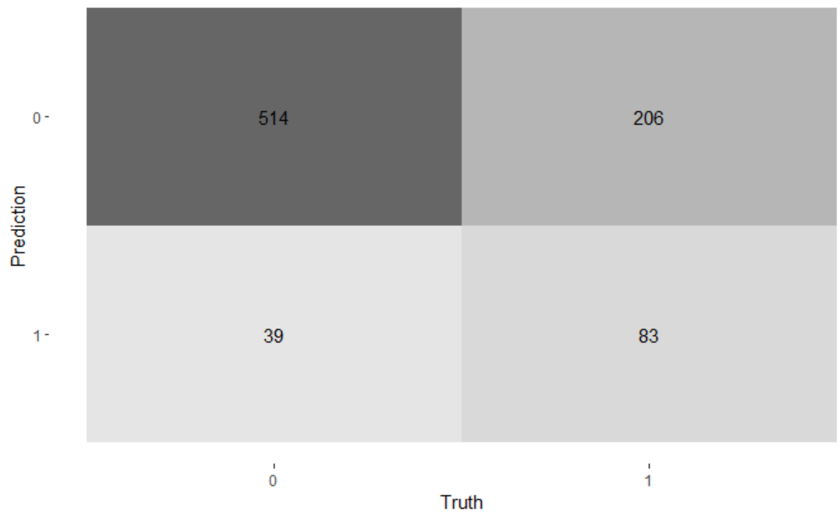


Precision: 0.7592257

Recall: 0.9653846

Accuracy: 0.7744399

Test Set Metrics & Confusion Matrix:

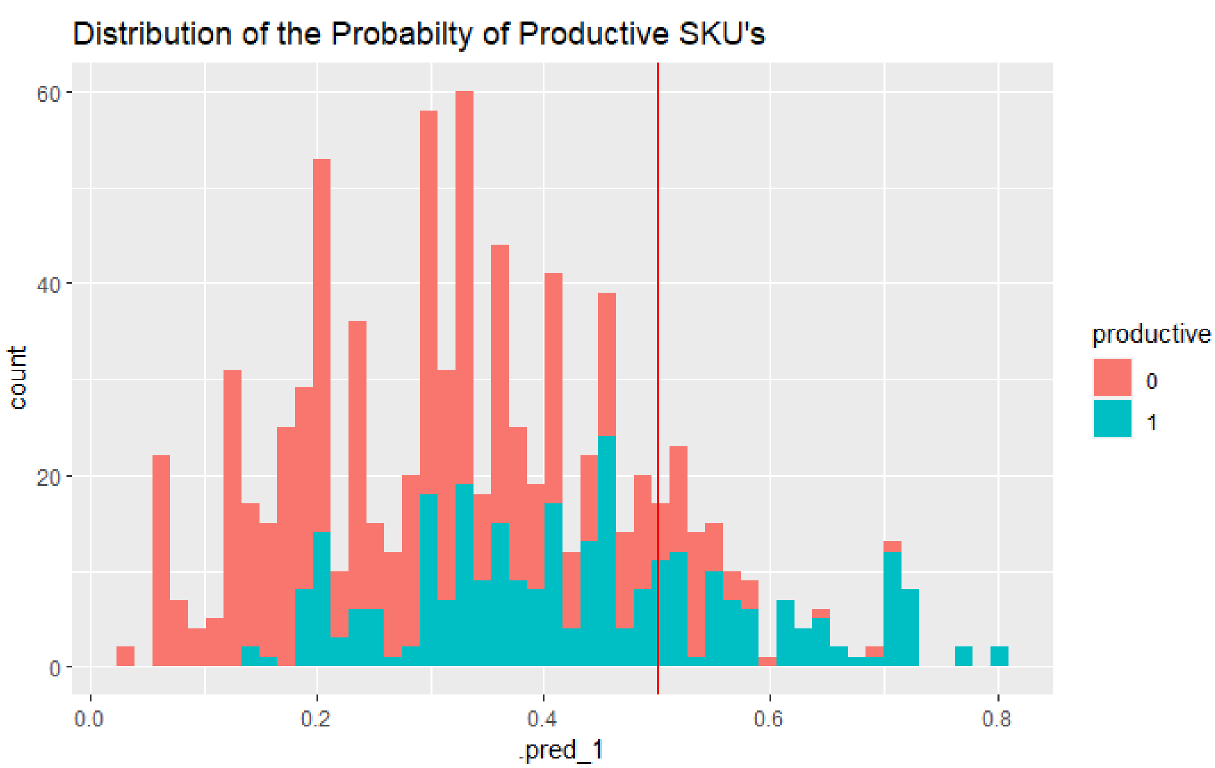


Precision: 0.7138889

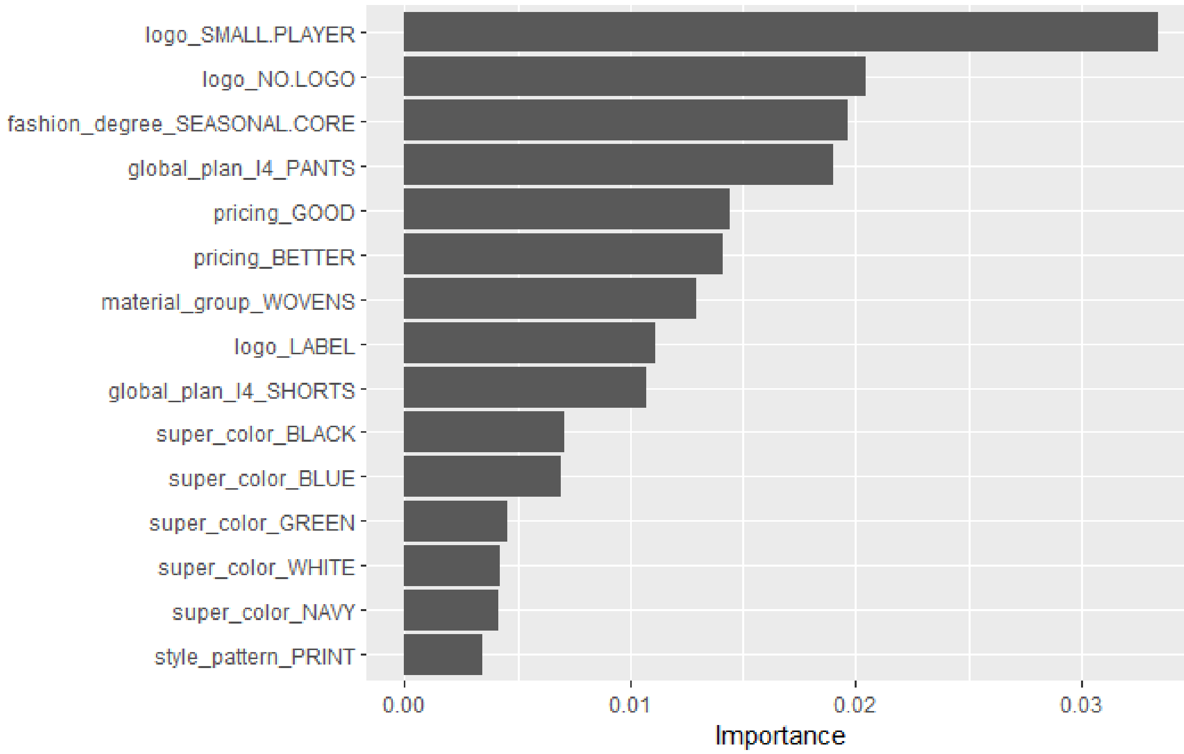
Recall: 0.9294756

Accuracy: 0.7090261

Distribution of Productive Probabilities:



Variable Importance:



The chart above shows the attributes that correlated the most with whether a unique SKU was found to be productive or not. This shows the variable importance for the analysis. The logo being the small player was fair and away the most important variable when it came to men's bottoms being productive SKUs. This could be something that Polo does regularly with men’s bottoms (a logo on the backside of the pants.) Bottoms having no logo were also found to be an important factor for men’s bottoms (perhaps both small logo and no logo are related to productive SKUs). Among fashion degrees, we can see that the fashion degree of seasonal core was related to productive SKUs. When it comes to unique and uncommon colors for pants, blue and green both stood out as variables that are related to productive SKUs.

<u>Womens Tops</u>

Used Variables

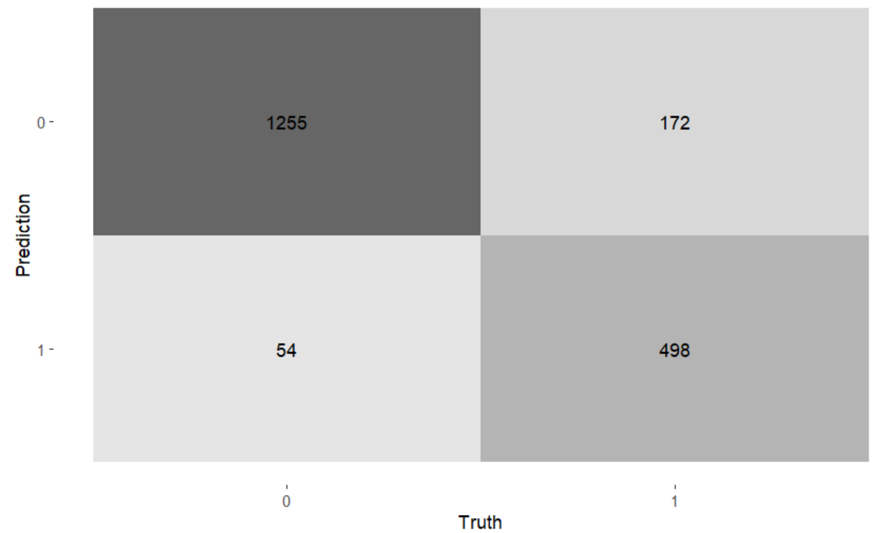
- **Fashion Degree:** seasonal, seasonal core, core
- **Fiber Content:** cotton, modal, linen, polyester, silk, leather/su, wool, cashmere, viscose
- **Global Plan L4:** polo shirt, sweaters, t-shirts, shirts
- **Logo:** rl metal,monogram, no logo, rl embroidery, branded, lrl monogram, novelty, other branding, small player, big player, polo bear, ranch brand,
- **Material Group:** sweaters, wovens, knits
- **Neckline:** crew neck, boat neck, turtle neck, polo knit collar, collar, not applicable, other, v neck, button down collar, tie, shawl collar, mock neck, band collar, polo self collar, split, square neck, scoop neck, ruffled, asymmetric, crew neck henley, hoodie, spread collar
- **Pricing:** good, better, best, luxury
- **Style Pattern:** solid, stripe, plaid/check, print, novelty, mixed media, heather/mélange, non-printed pattern, colorblock
- **Merch Fabrication:** jersey, mesh, interlock, twill, fleece, oxford, cotton, dbl knit, denim, terry, leather, poplin, wool, seersucker, cashmere, linen, corduroy, polyester, nylon, elastane, chambray
- **Super Color**

Final Model

Random Forest, trees = 1230, min_n = 2

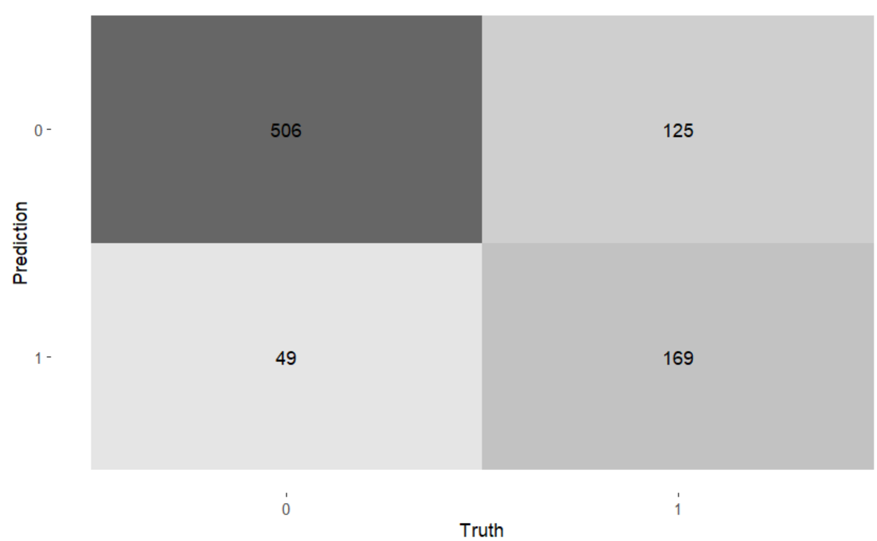
Training Set Metrics & Confusion Matrix

.metric <chr>	.estimator <chr>	.estimate <dbl>
accuracy	binary	0.8858009
kap	binary	0.7335645
mn_log_loss	binary	0.3515841
roc_auc	binary	0.9547735

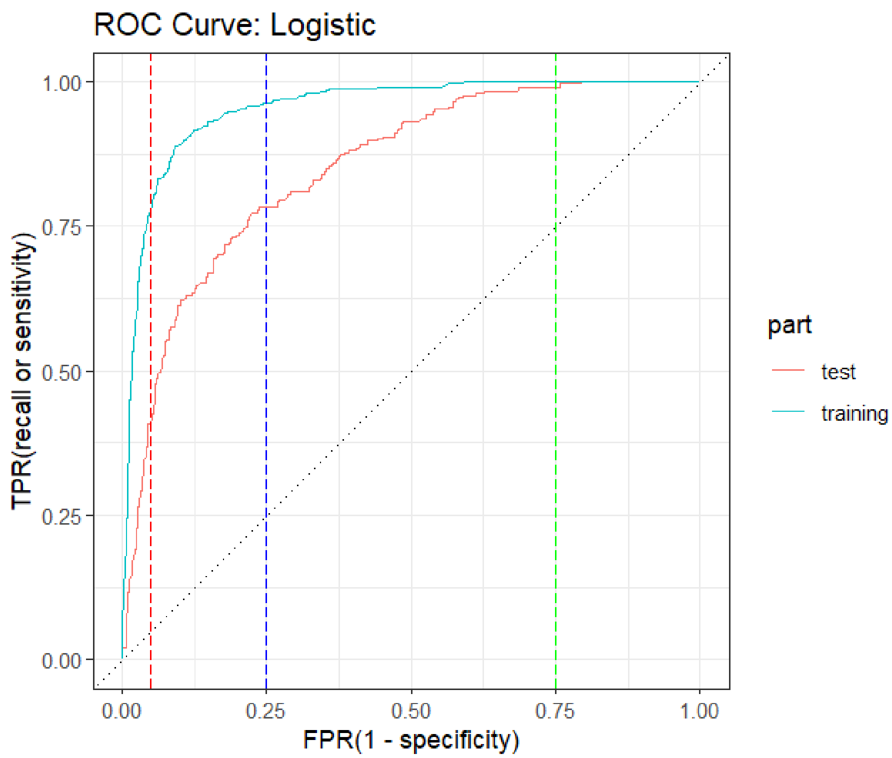


Testing Set Metrics & Confusion Matrix:

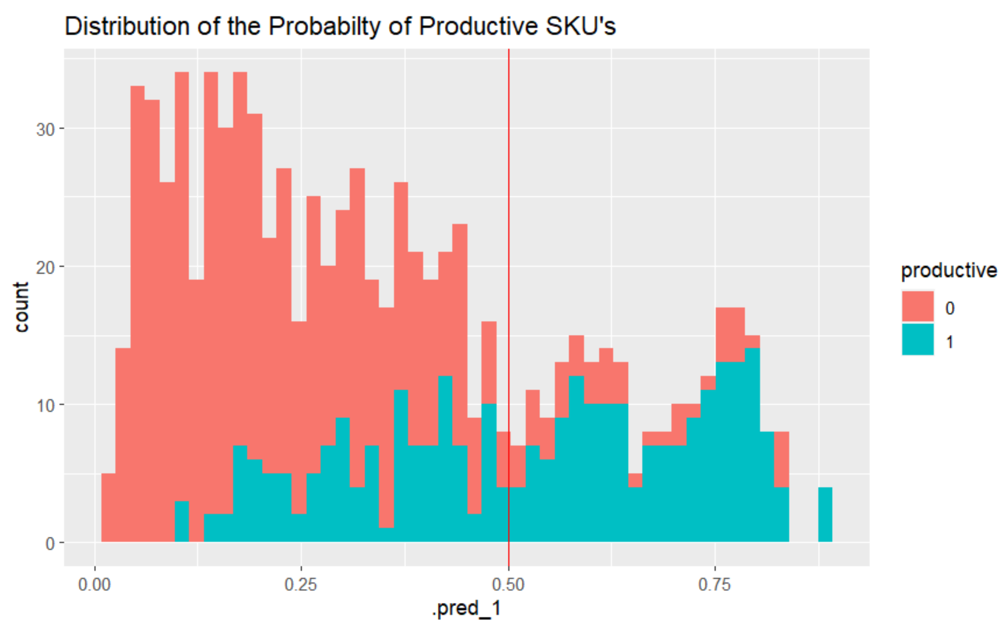
.metric <chr>	.estimator <chr>	.estimate <dbl>
accuracy	binary	0.8858009
kap	binary	0.7335645
mn_log_loss	binary	0.3515841
roc_auc	binary	0.9547735



ROC Curve (False Positive Rate on X Axis, True Positive Rate on Y Axis):

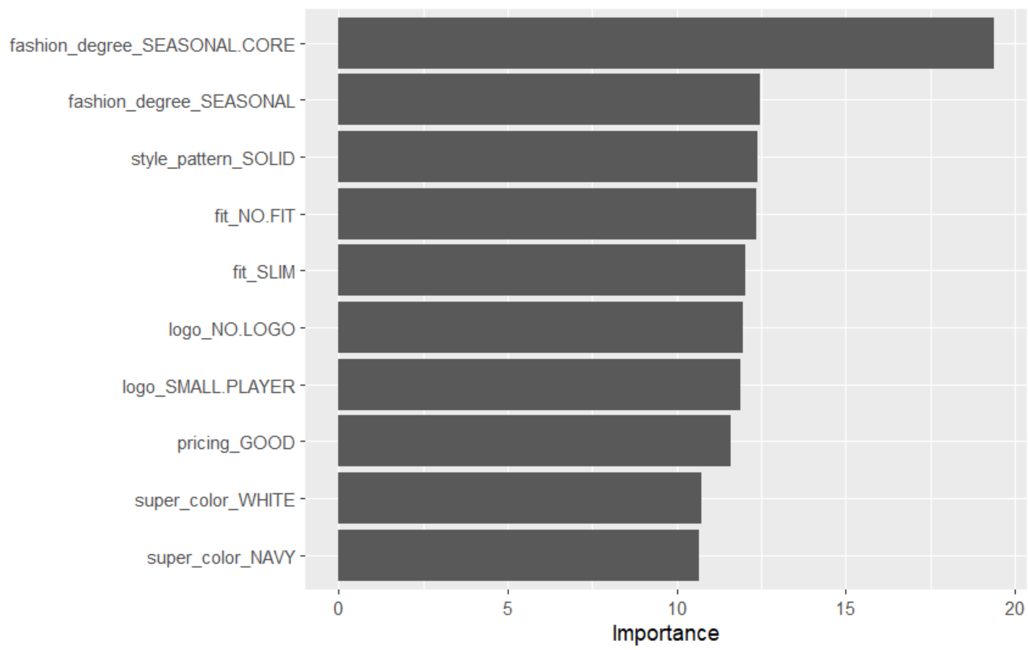


Distribution of Productive Probabilities:



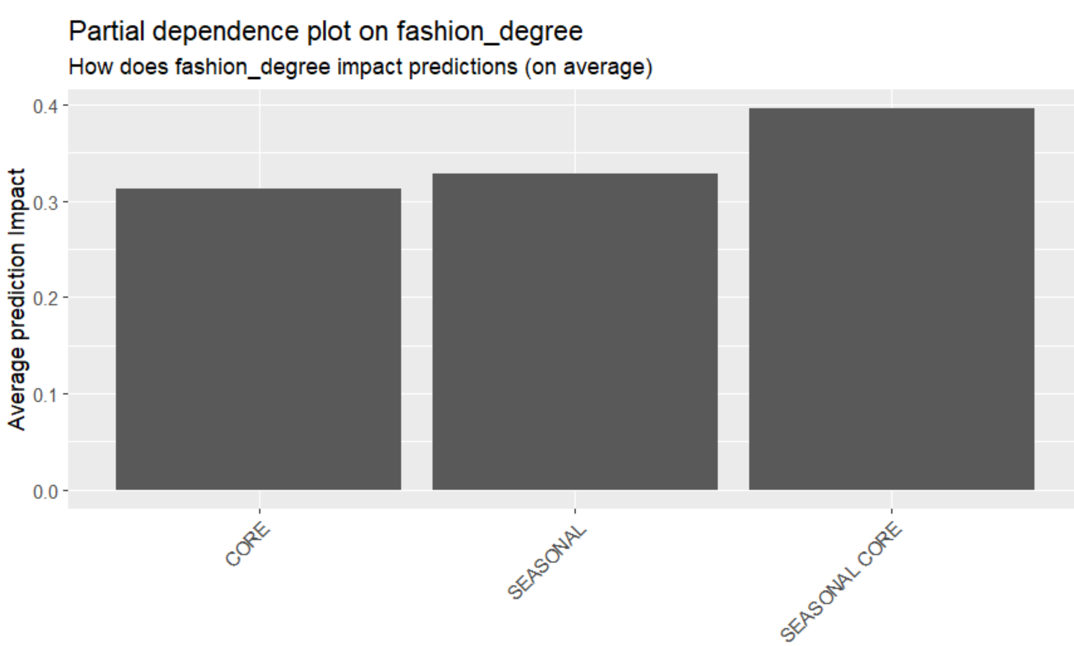
- pred_1 is the probability of productivity while the fill indicates the score of the product (1 for productive, 0 for unproductive)

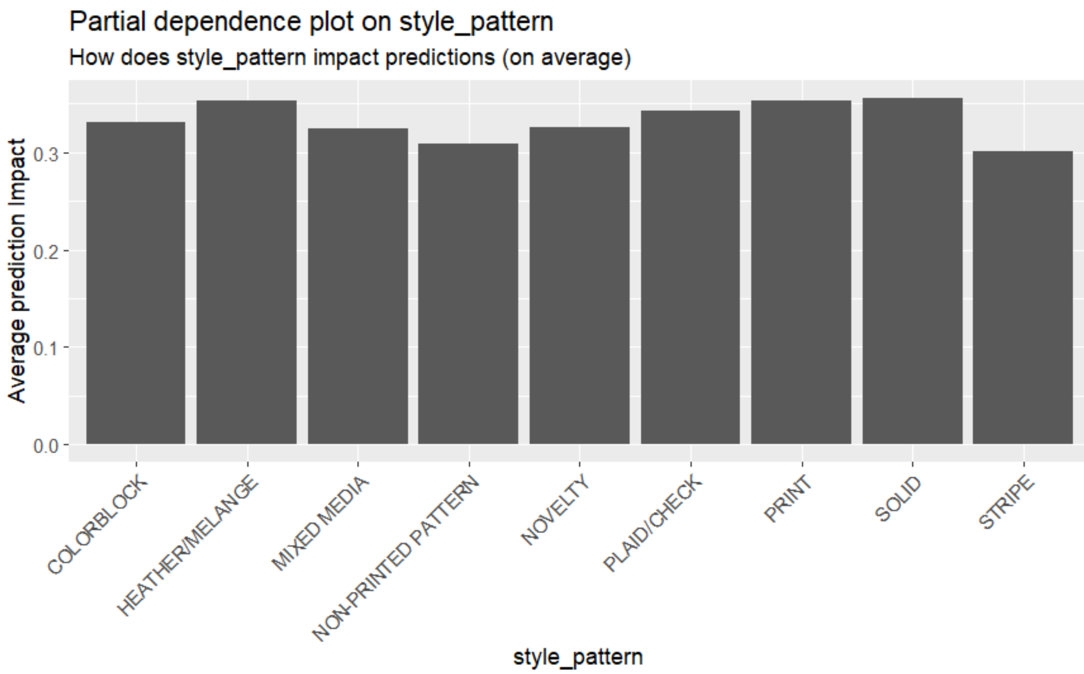
Variable Importance:

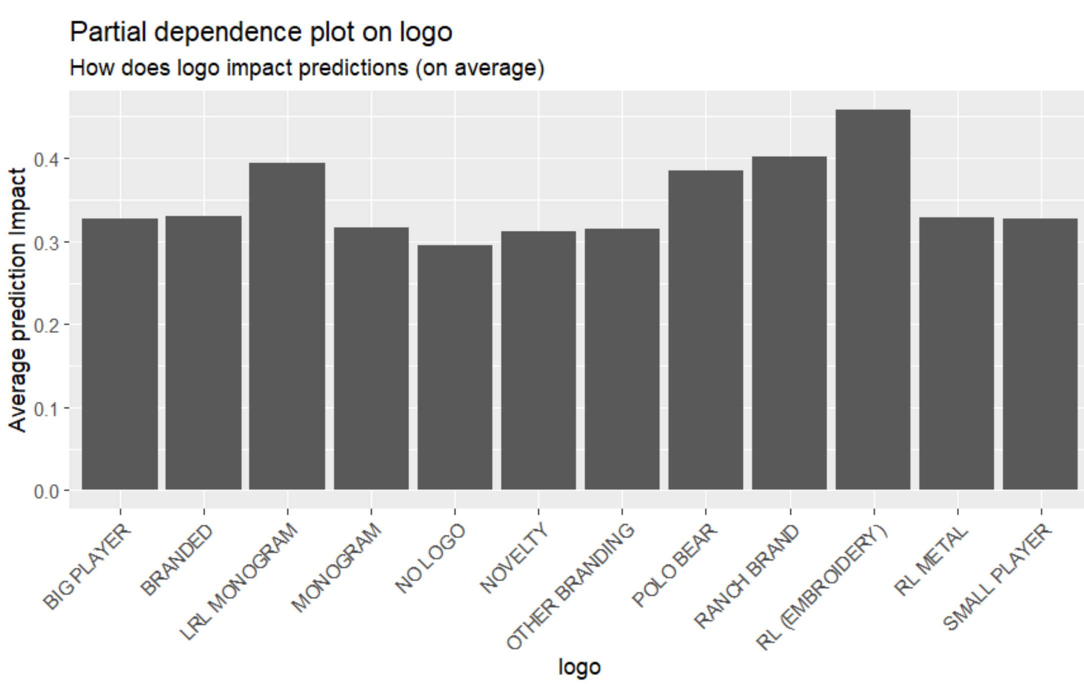


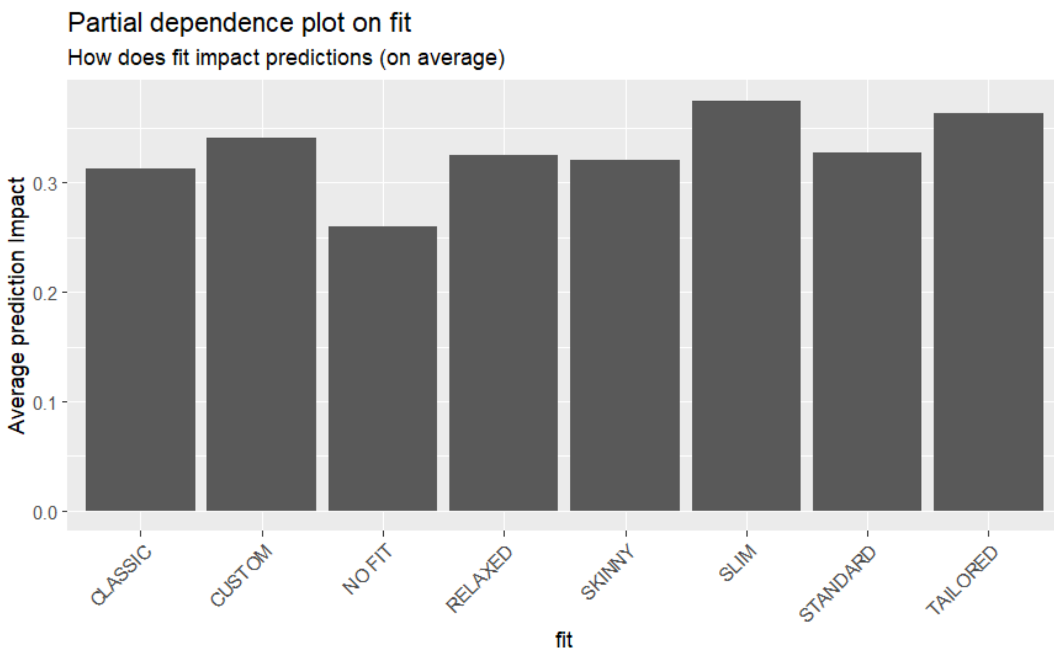
The chart above illustrates the variable importance and it's used to identify important features or variables in a dataset that contribute significantly to the prediction performance of a machine learning model.. It highlights the attributes that have the highest correlation with productivity. According to the graph, women's tops are highly influenced by seasonal trends, with solid to be the style pattern. Additionally, no logo, small player logo, or white and navy super color are generally more favorable in terms of productivity.

Partial Dependency Plots:

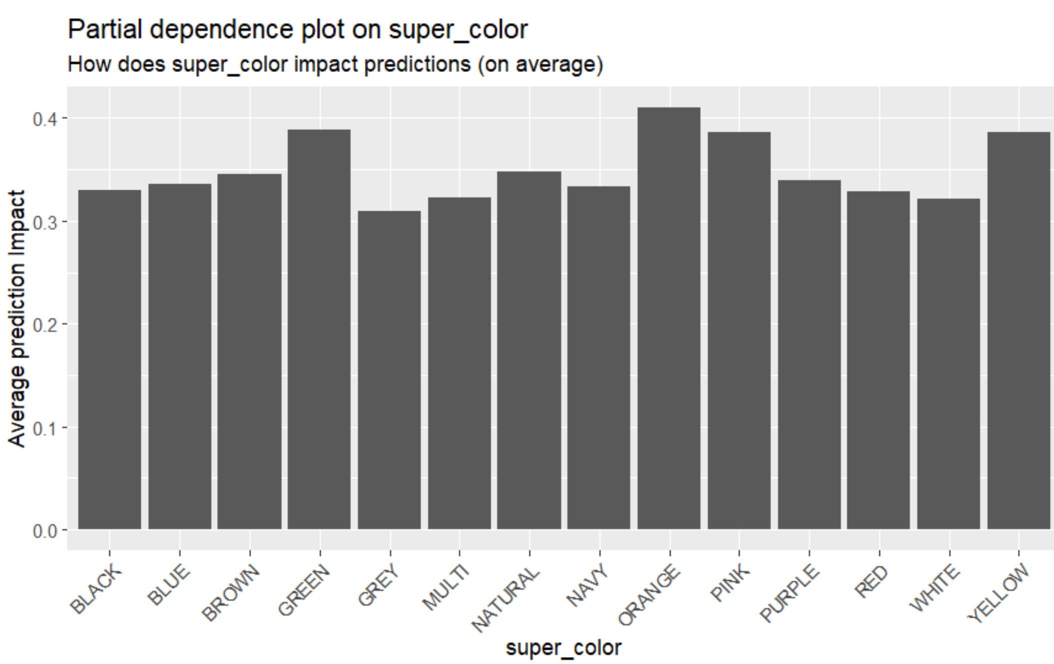



Partial dependence plot on style_pattern
How does style_pattern impact predictions (on average)
Average prediction Impact
0.0
0.1
0.2
0.3
COLORBLOCK
HEATHER/MELANGE
MIXED MEDIA
NON-PRINTED PATTERN
NOVELTY
PLAID/CHECK
PRINT
SOLID
STRIPE
style_pattern


Partial dependence plot on logo
How does logo impact predictions (on average)
Average prediction Impact
0.0
0.1
0.2
0.3
0.4
BIG PLAYER
BRANDED
LRL MONOGRAM
MONOGRAM
NO LOGO
NOVELTY
OTHER BRANDING
POLO BEAR
RANCH BRAND
RL (EMBROIDERY)
RL METAL
SMALL PLAYER
logo

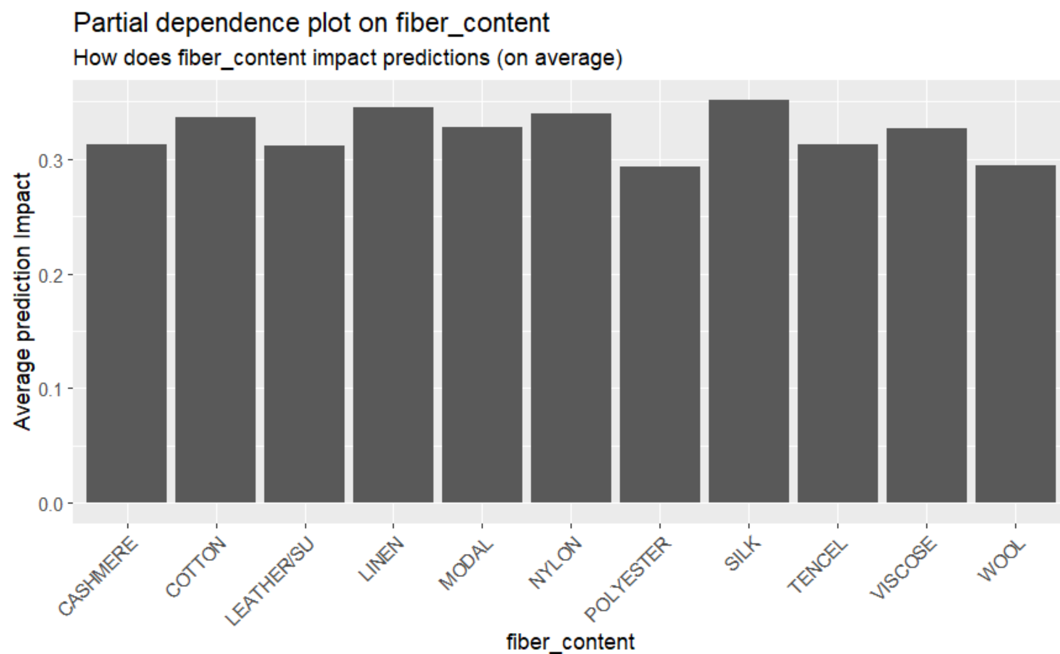


Partial dependence plot on fit
How does fit impact predictions (on average)
Average prediction Impact
0.0
0.1
0.2
0.3
CLASSIC
CUSTOM
NO FIT
RELAXED
SKINNY
SLIM
STANDARD
TAILORED
fit



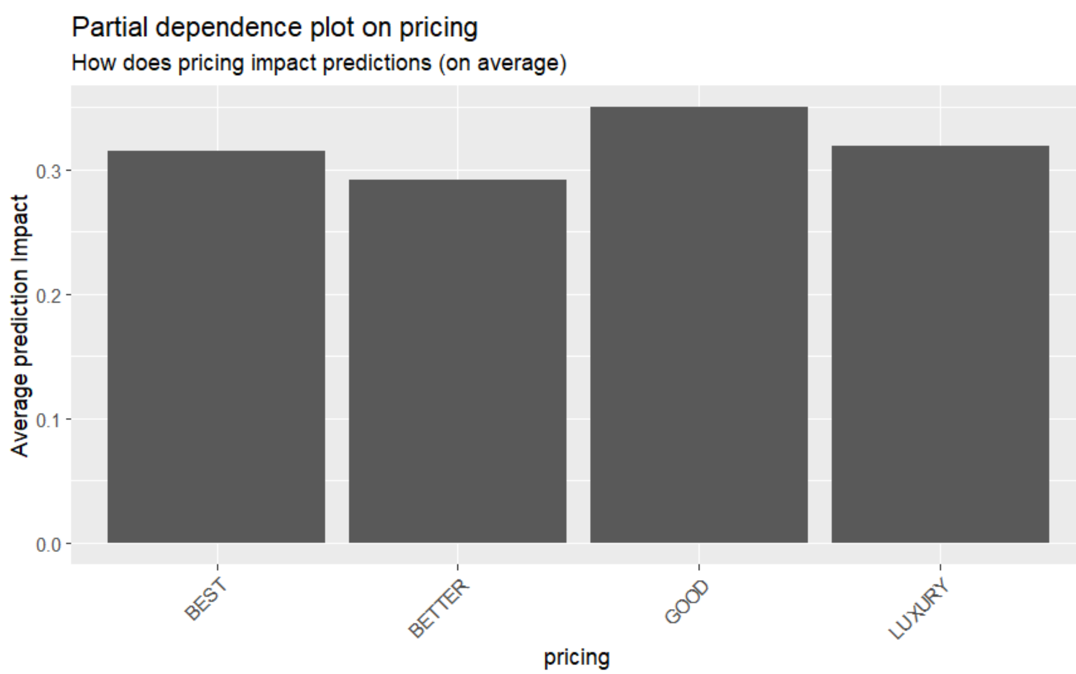
Partial dependence plot on super_color
How does super_color impact predictions (on average)
Average prediction Impact
0.0
0.1
0.2
0.3
0.4
BLACK
BLUE
BROWN
GREEN
GREY
MULTI
NATURAL
NAVY
ORANGE
PINK
PURPLE
RED
WHITE
YELLOW
super_color

The plots above illustrate the mean likelihood of achieving a certain level of productivity within a specific attribute, while keeping all other variables constant. For example, the super color plot shows that orange women's tops have an average 41% probability of achieving a global SKU score of 1, 2, 3, or 4, according to the model. By comparison, yellow and green women's tops have a 38% probability of being productive. This suggests that, on average, orange tops have a 3% higher likelihood of being productive



than yellow and green tops.

It's important to note that this is a summary view, where each product in a category is scored while holding all other attributes constant, and then an average of those scores is



taken. This method is particularly useful in visualizing complex machine learning techniques, such as random forests, that can be difficult to interpret.

Womens Bottoms

Used Variables

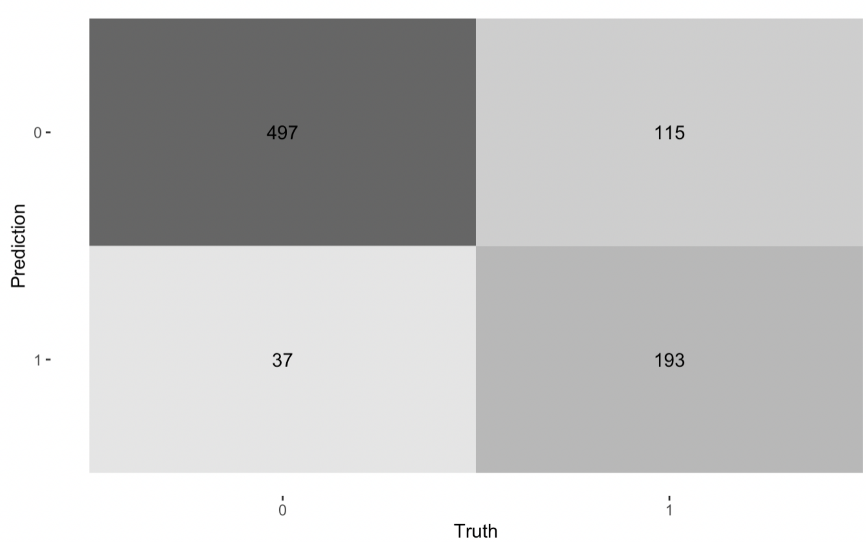
- **Fashion Degree:** seasonal, seasonal core, core
- **Fiber Content:** acetate, cashmere, cotton, leather, linen, nylon, polyester, silk. tencel, viscose, wool
- **Material Group:** wovens, sweaters, knits, skins
- **Global Plan L4:** pants, jeans
- **Logo:** big player, branded, label, monogram, no logo, novelty, other branding, rl (embroidery), small player
- **Pricing:** good, better, best, luxury
- **Style Pattern:** colorblock, heather/melange, non-printed pattern, novelty, plaid/check, print, solid, stripe
- **Super Color**

Final Model

Random Forest trees= 1472, min_n= 2

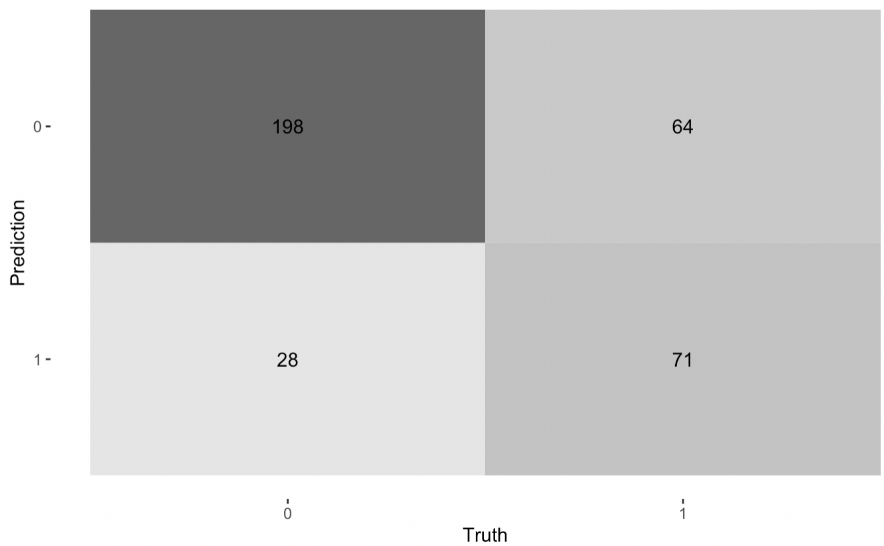
Training Set Metrics & Confusion Matrix:

.metric <chr>	.estimator <chr>	.estimate <dbl>
accuracy	binary	0.8194774
kap	binary	0.5888936
mn_log_loss	binary	0.4081952
roc_auc	binary	0.9136023

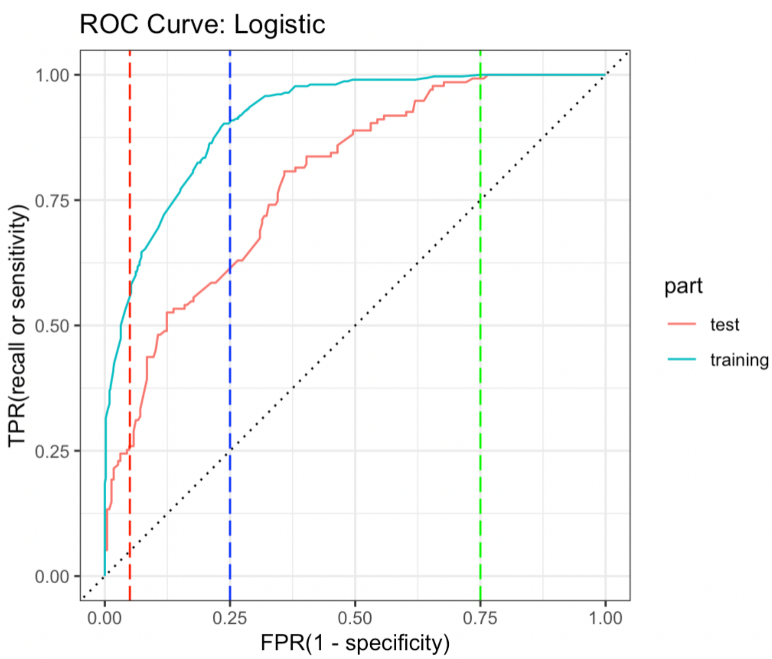


Test Set Metrics & Confusion Matrix:

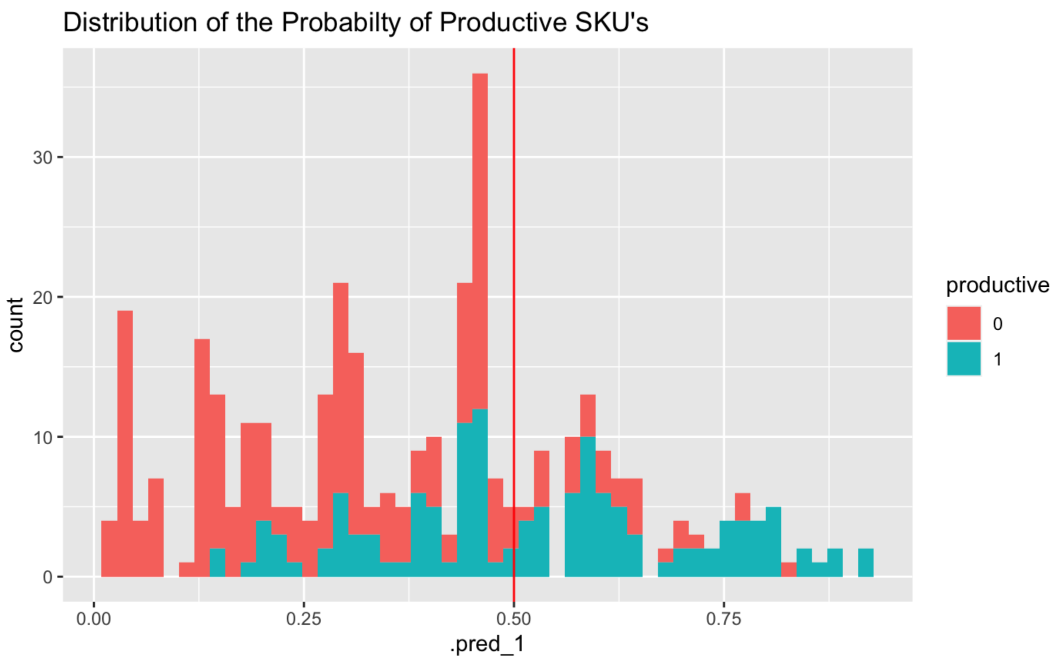
.metric <chr>	.estimator <chr>	.estimate <dbl>
accuracy	binary	0.7451524
kap	binary	0.4248407
mn_log_loss	binary	0.5208396
roc_auc	binary	0.7896100



ROC Curve (False Positive Rate on X Axis, True Positive Rate on Y Axis):

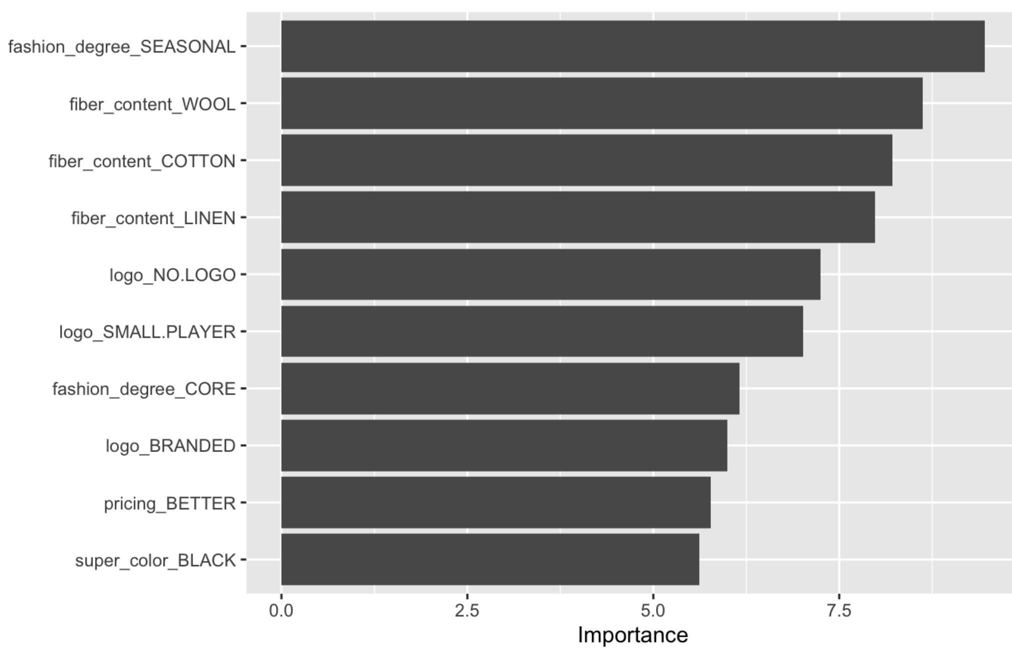


Distribution of Productive Probabilities:



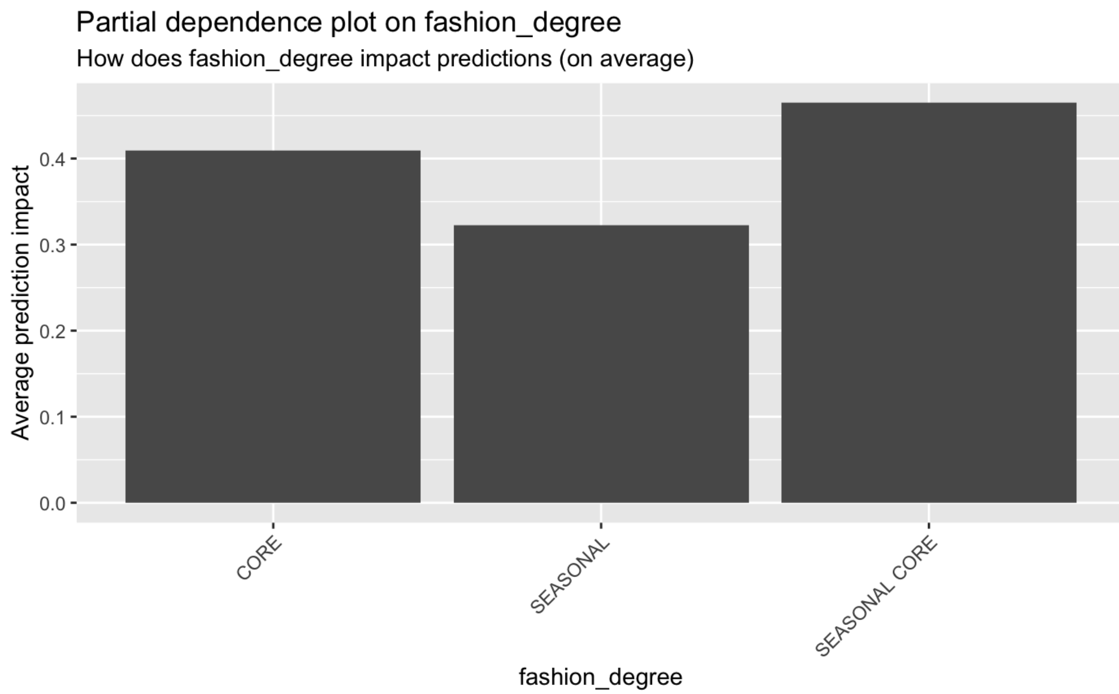
- pred_1 is the probability of productivity while the fill indicates the score of the product (1 for productive, 0 for unproductive)

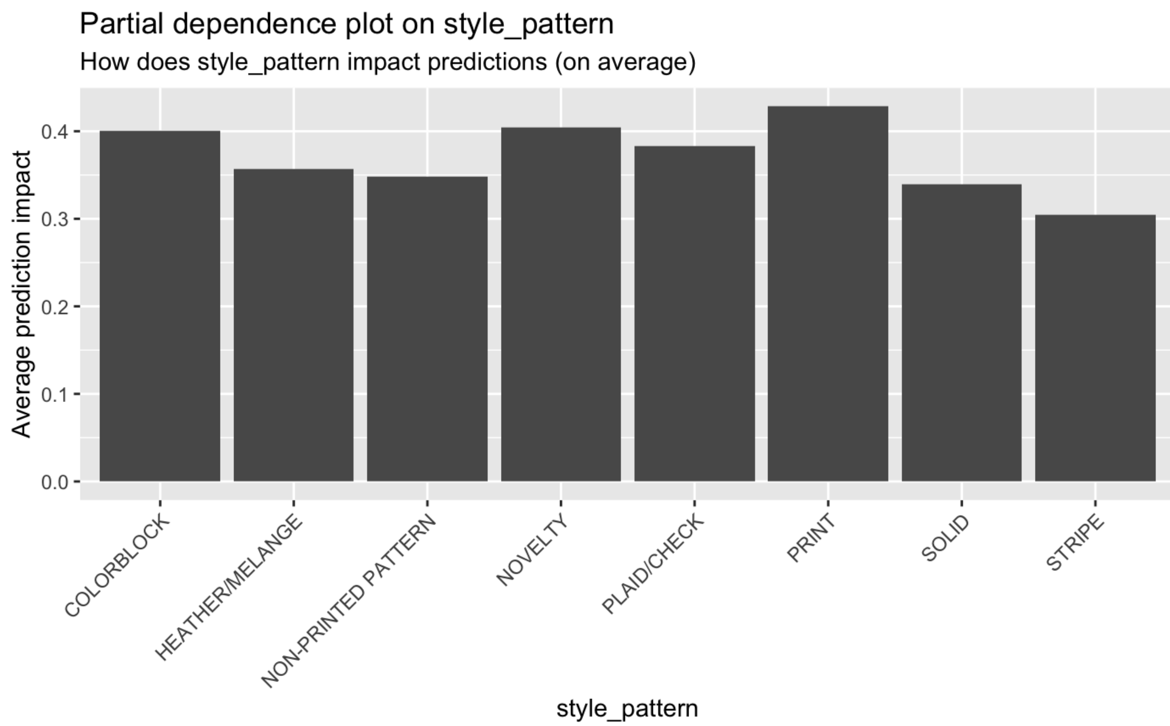
Variable Importance:

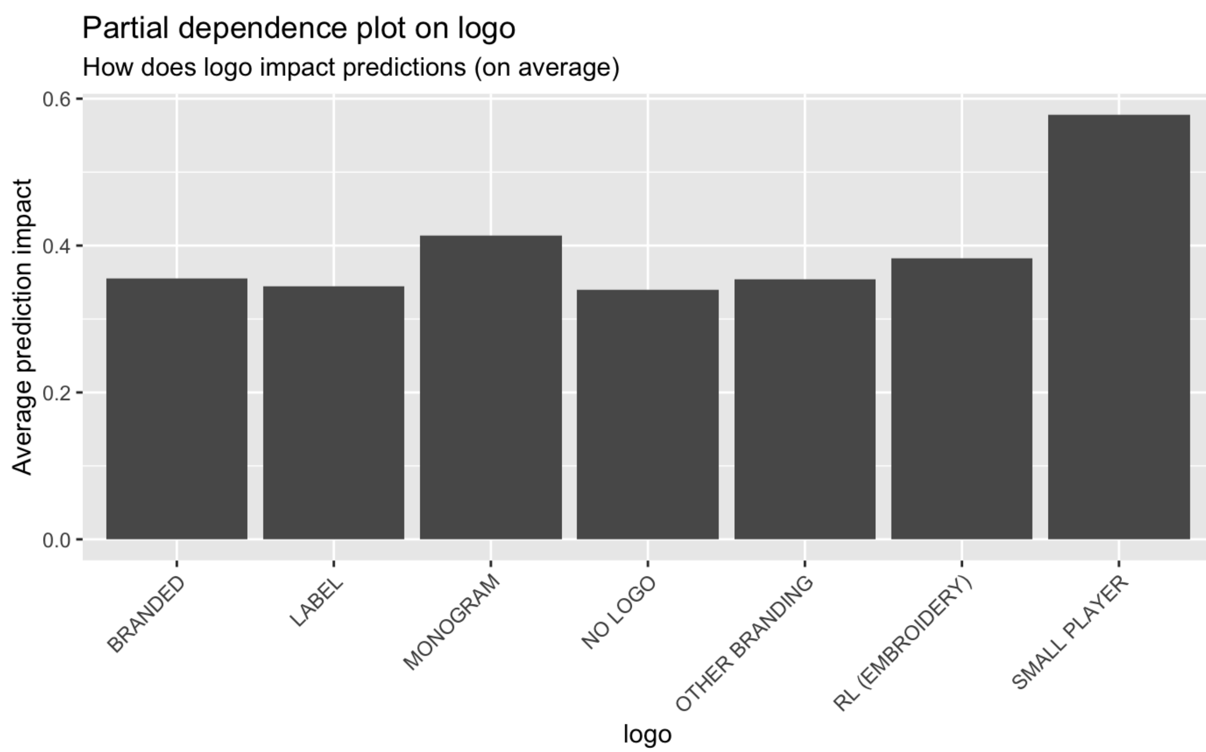


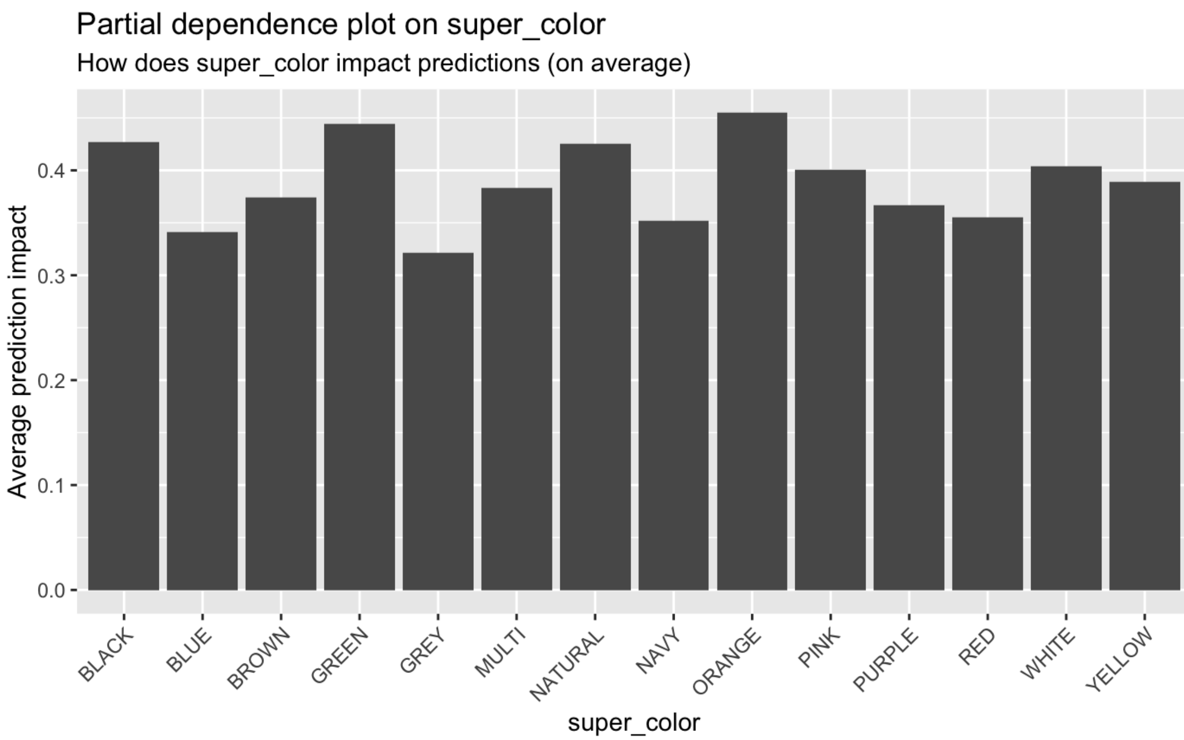
The chart above illustrates the variable importance in determining whether a unique SKU is productive or not. It highlights the attributes that have the highest correlation with productivity. According to the graph, women's bottoms are highly influenced by seasonal trends, with wool, cotton, and linen being the most productive fiber contents. Additionally, no logo, small logo, or branded designs are generally more favorable in terms of productivity.

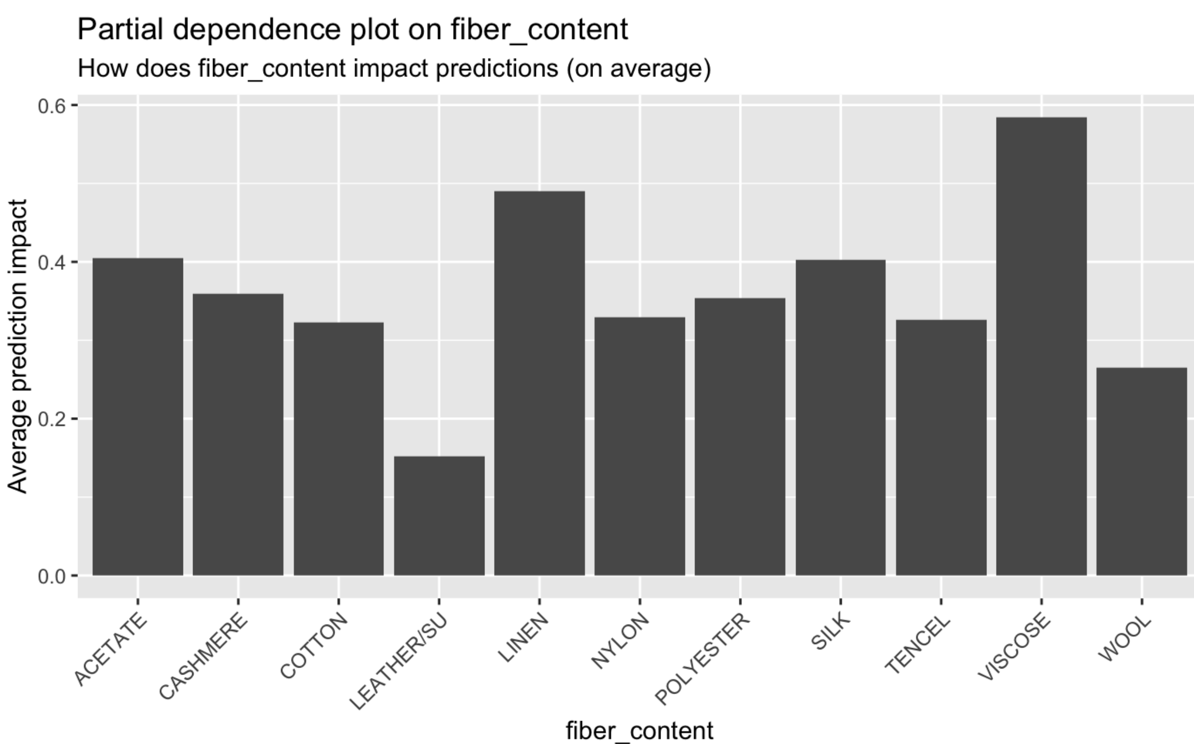
Partial Dependency Plots:




Partial dependence plot on style_pattern
How does style_pattern impact predictions (on average)
Average prediction impact
0.0
0.1
0.2
0.3
0.4
COLORBLOCK
HEATHER/MELANGE
NON-PRINTED PATTERN
NOVELTY
PLAID/CHECK
PRINT
SOLID
STRIPE
style_pattern


Partial dependence plot on logo
How does logo impact predictions (on average)
Average prediction impact
0.0
0.2
0.4
0.6
BRANDED
LABEL
MONOGRAM
NO LOGO
OTHER BRANDING
RL (EMBROIDERY)
SMALL PLAYER
logo





The above plots display the average probability of productivity of a specific level within an attribute while keeping all other factors constant. For instance, looking at the super color plot, we can observe that, on average, pink women's bottoms have a 40% probability of achieving a global SKU score of 1, 2, 3, or 4 based on the model. In comparison, orange women's bottoms have a 45% probability of being productive. Therefore, we can infer that orange bottoms have a 5% higher probability of being productive than pink bottoms on average.

Again, it is important to note that this is an aggregate view. There are many orange bottoms that are not productive, just as there are many pink bottoms that are. This method examines the score assigned to each product within a category while holding every other attribute constant and takes an average of that score. It's particularly valuable in deciphering complex "black box" machine learning techniques, such as the random forest.

Growth Market: Men Outerwear

Used Variables

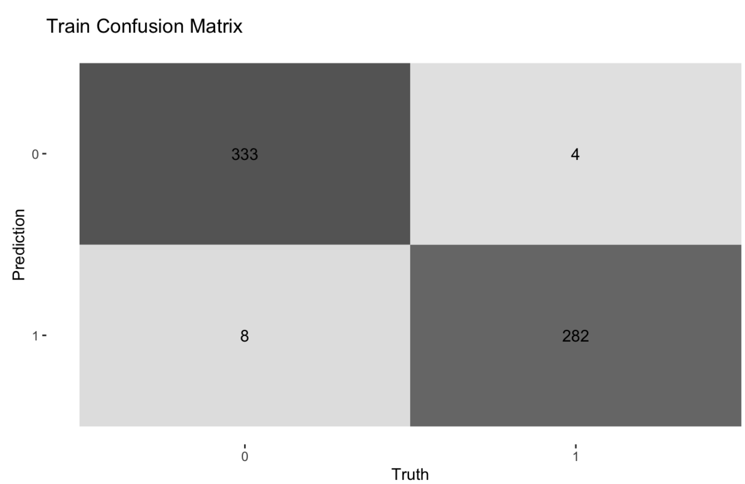
- **Fashion Degree:** seasonal, seasonal core, core
- **Fiber Content:** leather, polyethylene, nylon, polyester, linen, wool, cotton
- **Global Plan L4:** outerwear
- **Fit:** No fit, standard, custom slim, classic
- **Material Group:** wovens, sweaters, knits, skins
- **Logo:** big player, branded, label, monogram, no logo, novelty, other branding, rl (embroidery), small player
- **Merch Fabrication:** twill, poplin, chamray, herringbone, denim, ripstop
- **Pricing:** good, better, best, luxury
- **Style Pattern:** colorblock, heather/melange, non-printed pattern, novelty, plaid/check, print, solid, stripe
- **Super Color**

Final Model

XGBoost trees = 200, learn rate = 0.3103493

Training Set Metrics & Confusion Matrix:

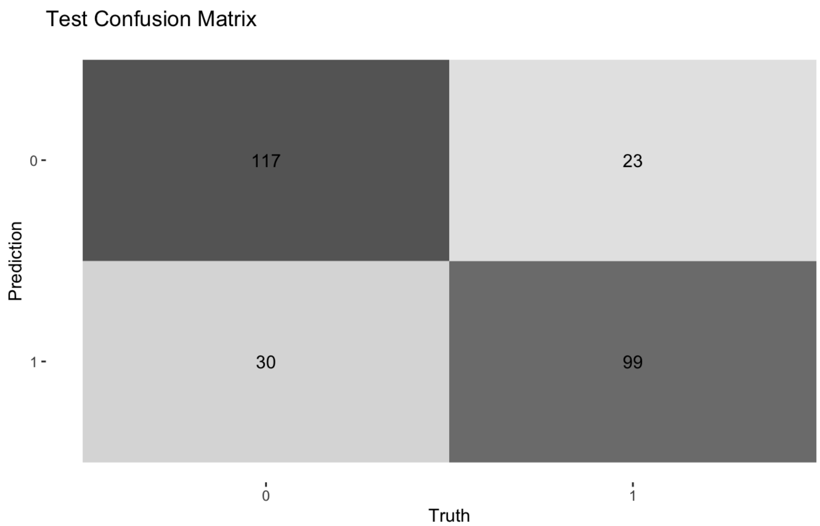
.estimator <chr>	part <chr>	accuracy <dbl>	kap <dbl>	mn_log_loss <dbl>	roc_auc <dbl>
binary	training	0.9808612	0.9614691	0.08074392	0.9981800



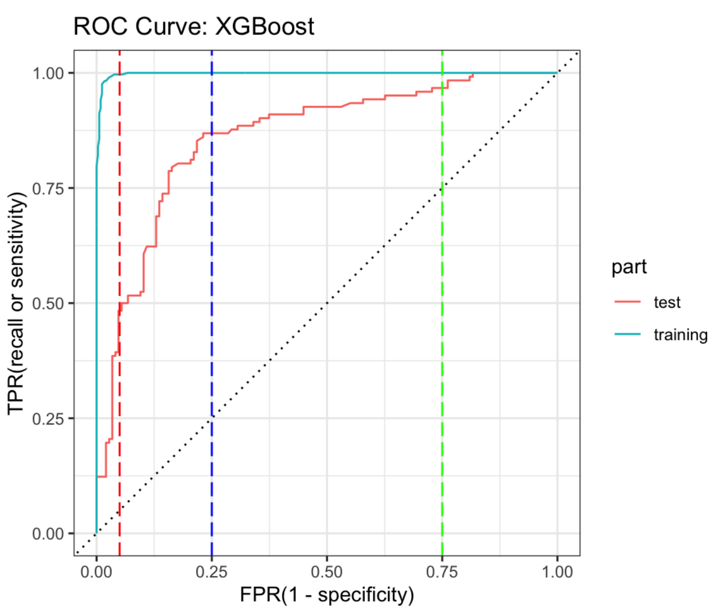
Test Set Metrics & Confusion Matrix:

.estimator <chr>	part <chr>	accuracy <dbl>	kap <dbl>	mn_log_loss <dbl>	roc_auc <dbl>

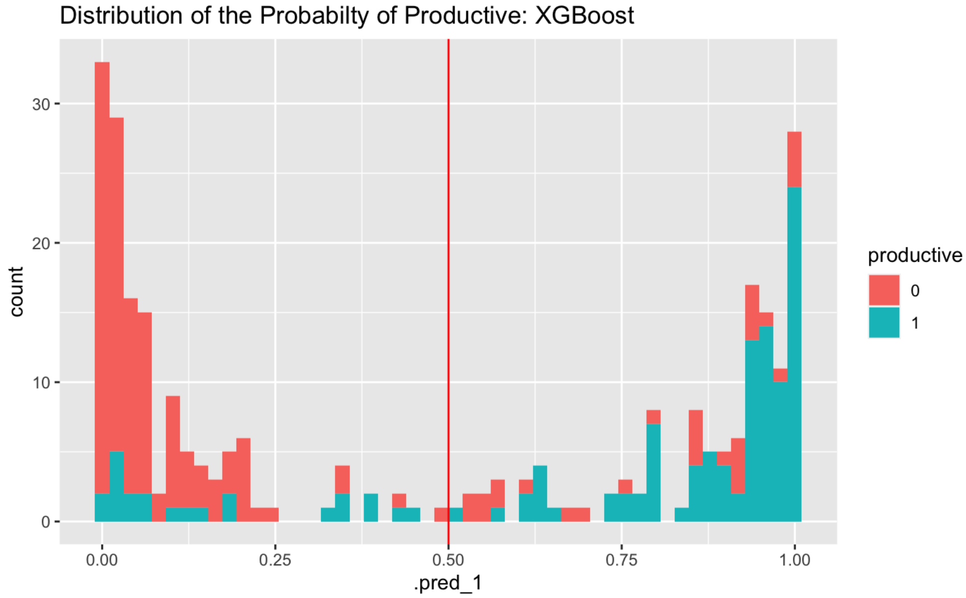
binary	testing	0.8029740	0.6044447	0.54430517	0.8619382



ROC Curve (False Positive Rate on X Axis, True Positive Rate on Y Axis):

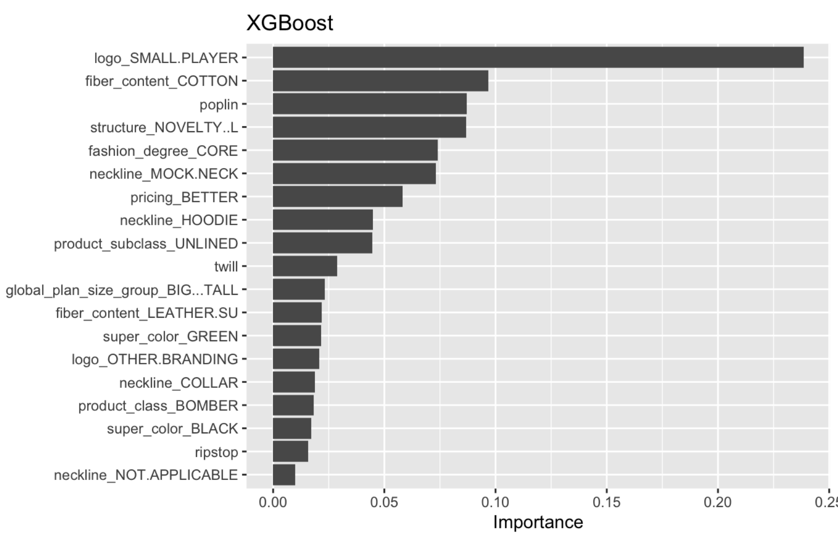


Distribution of Productive Probabilities:



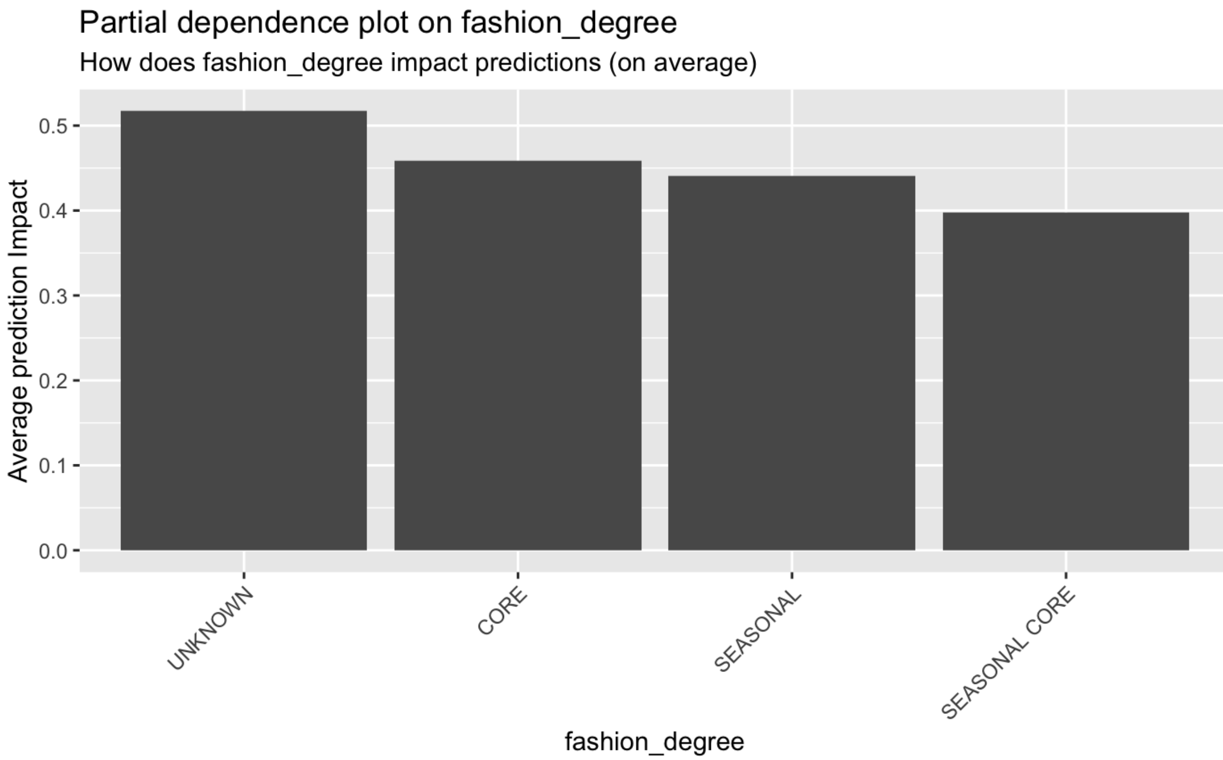
- pred_1 is the probability of productivity while the fill indicates the score of the product (1 for productive, 0 for unproductive)

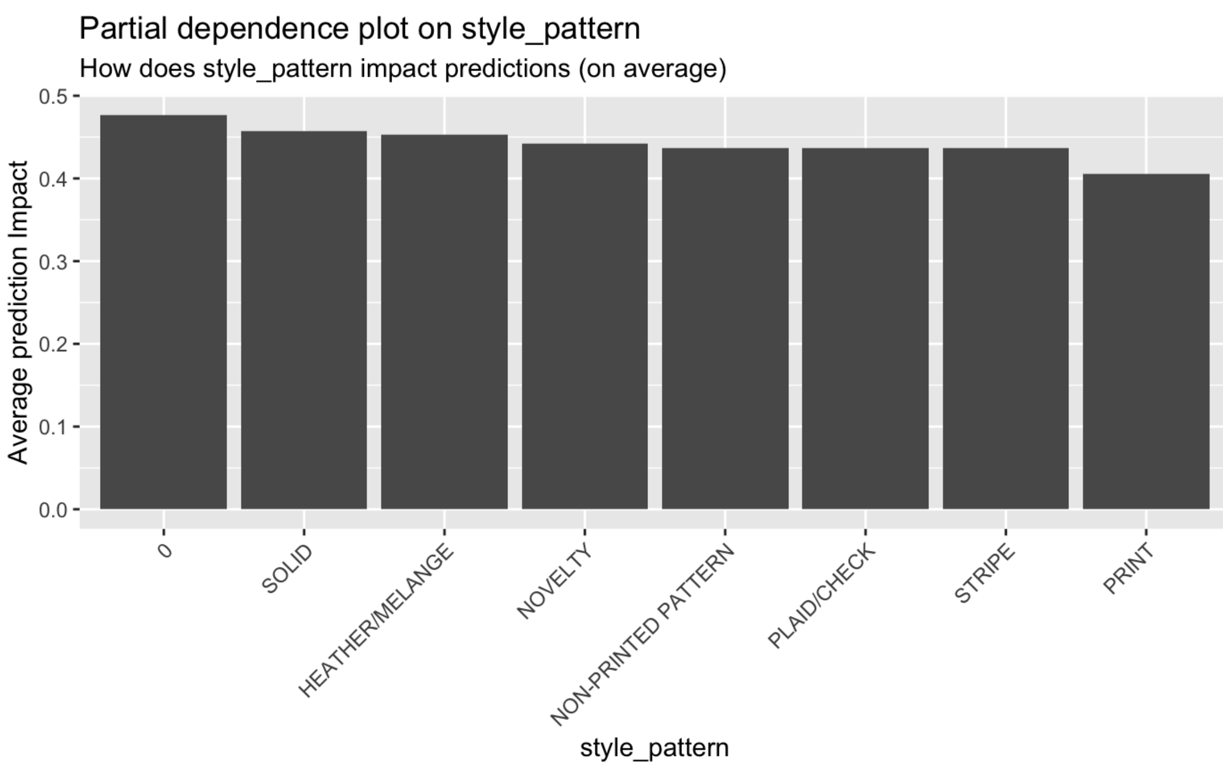
Variable Importance:

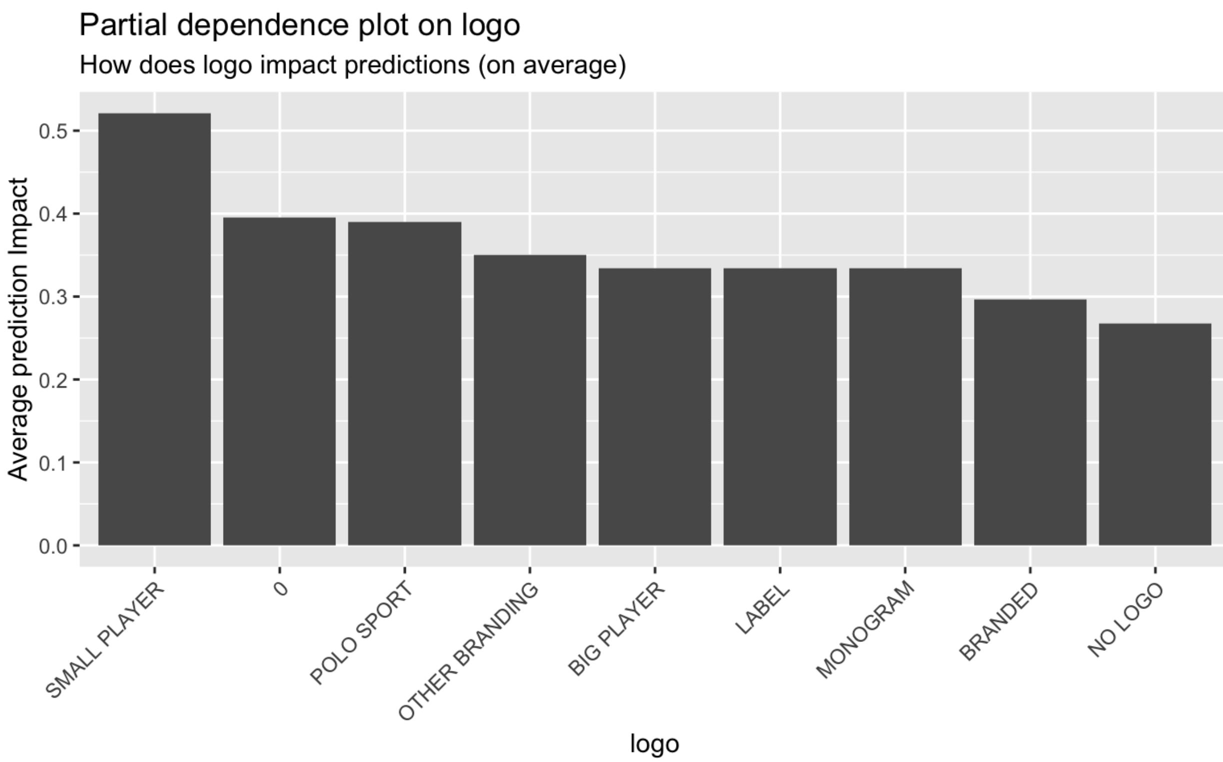


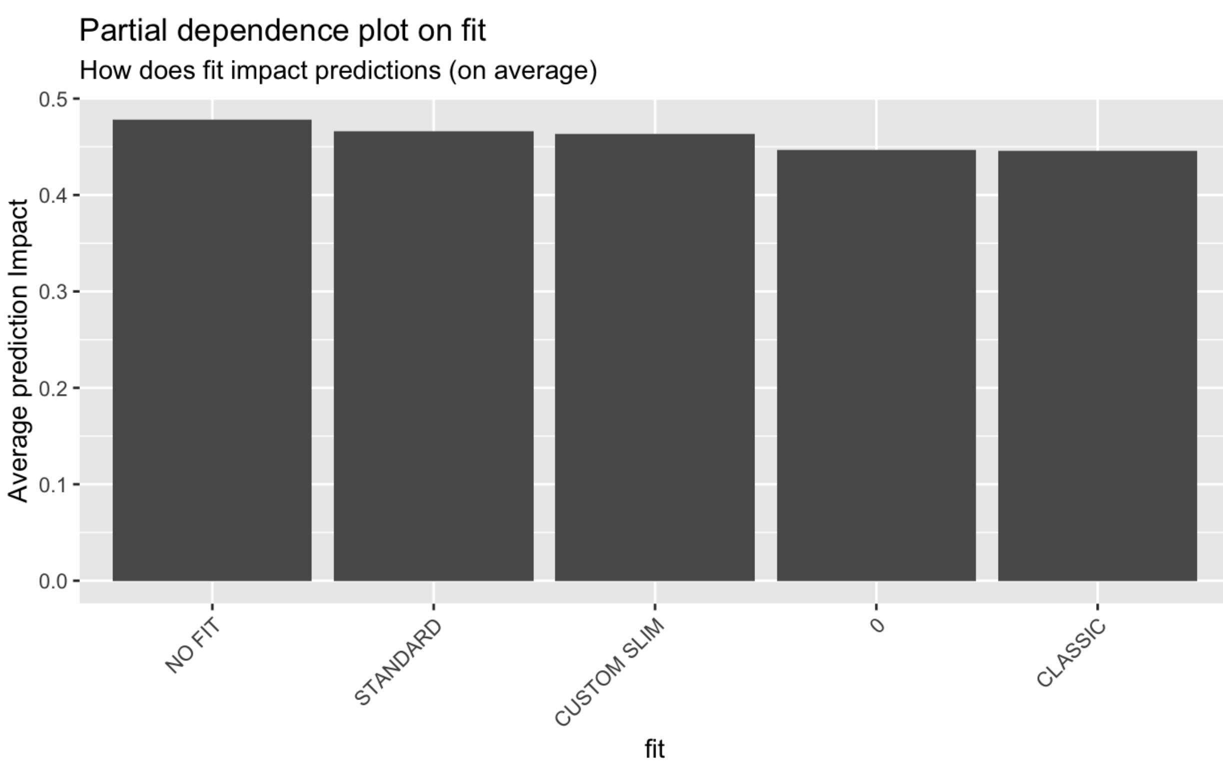
The chart above illustrates the variable importance in determining whether a unique SKU is productive or not. It highlights the attributes that have the highest correlation with productivity. According to the graph, men's outerwears are highly influenced by logo and fiber contents, with core, poplin, and mock neck being the most productive features. Additionally, better pricing, hoodie, or twill designs are generally more favorable in terms of productivity.

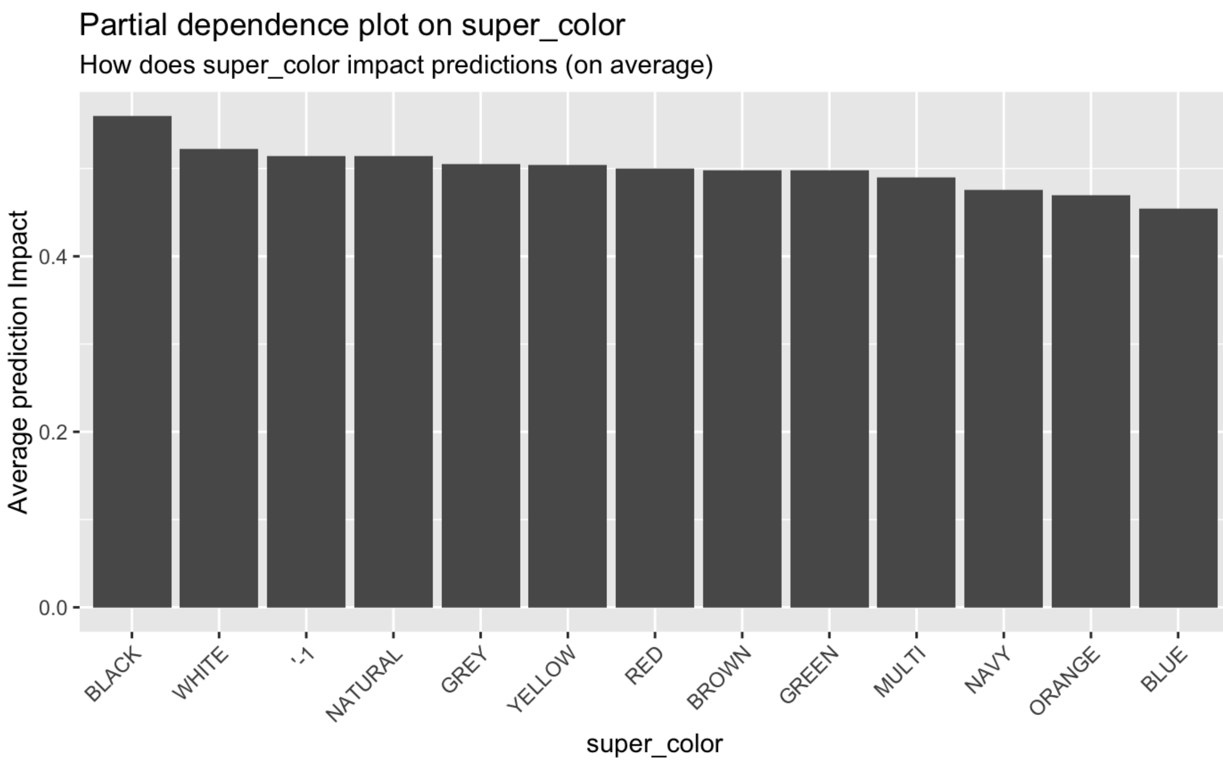
Partial Dependency Plots:

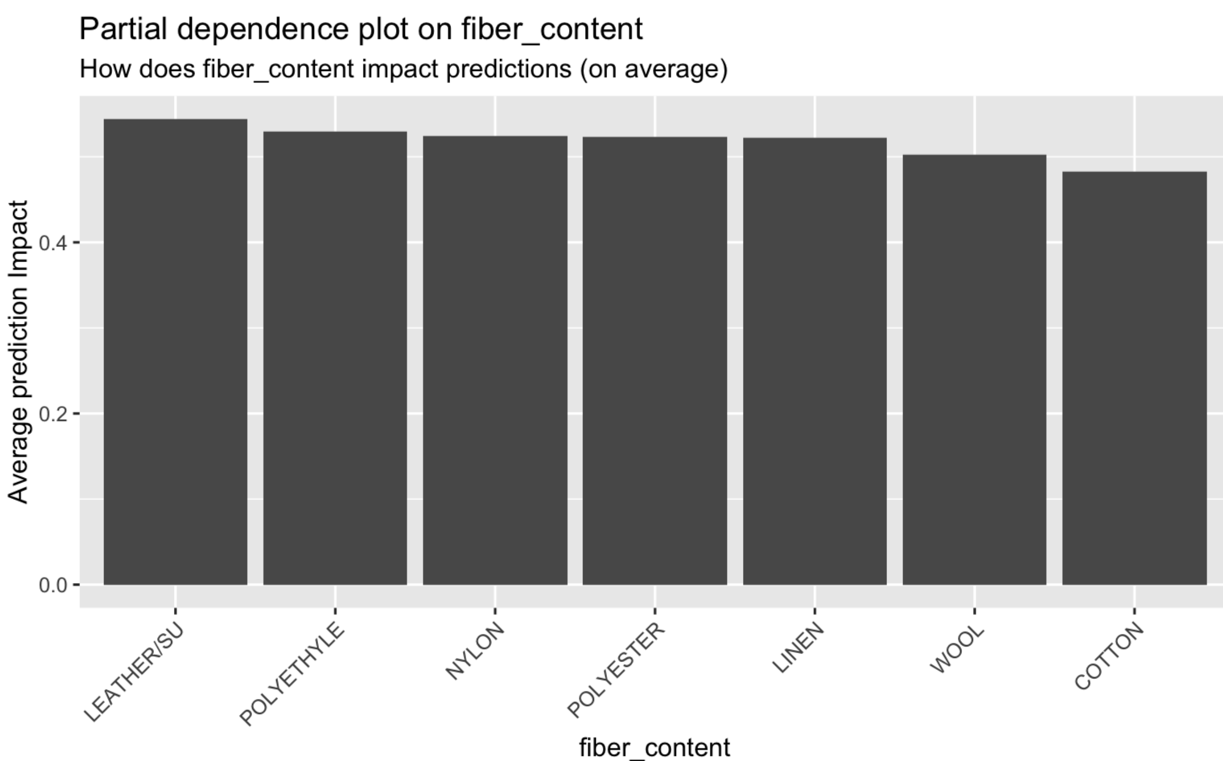


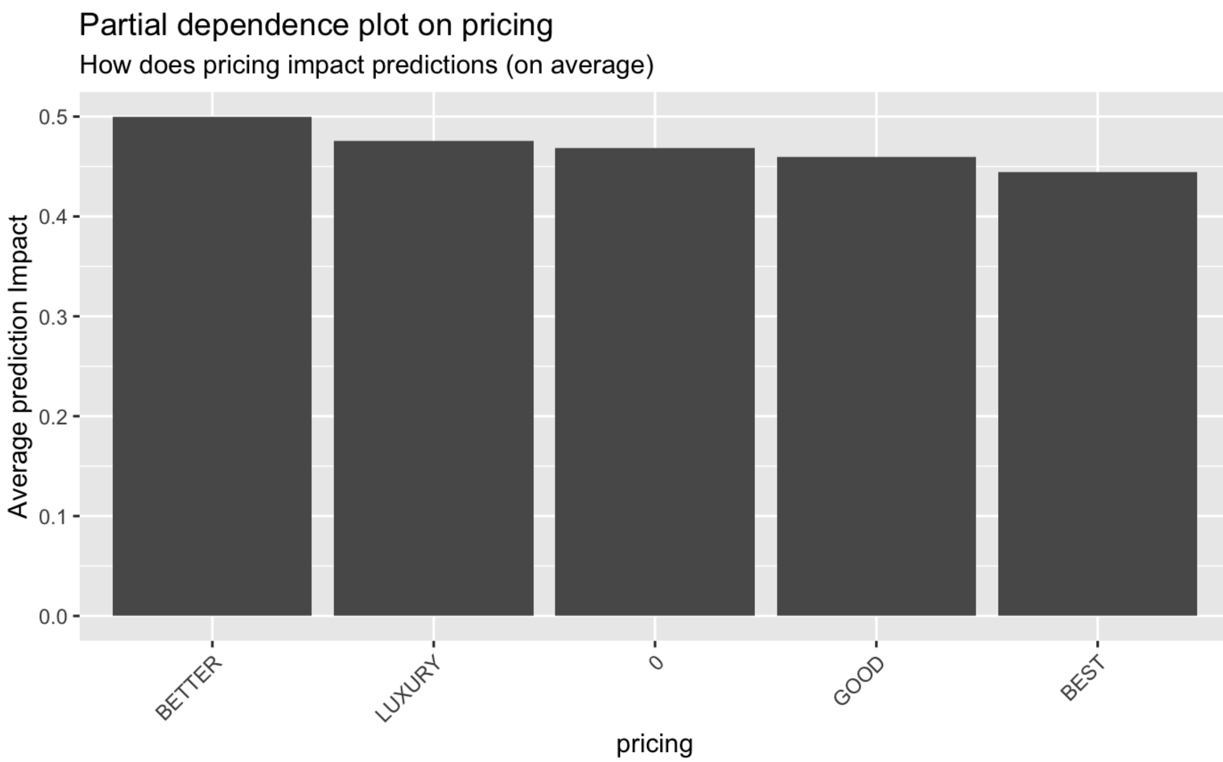



Partial dependence plot on logo
How does logo impact predictions (on average)
Average prediction Impact
0.0
0.1
0.2
0.3
0.4
0.5
SMALL PLAYER
0
POLO SPORT
OTHER BRANDING
BIG PLAYER
LABEL
MONOGRAM
BRANDED
NO LOGO
logo

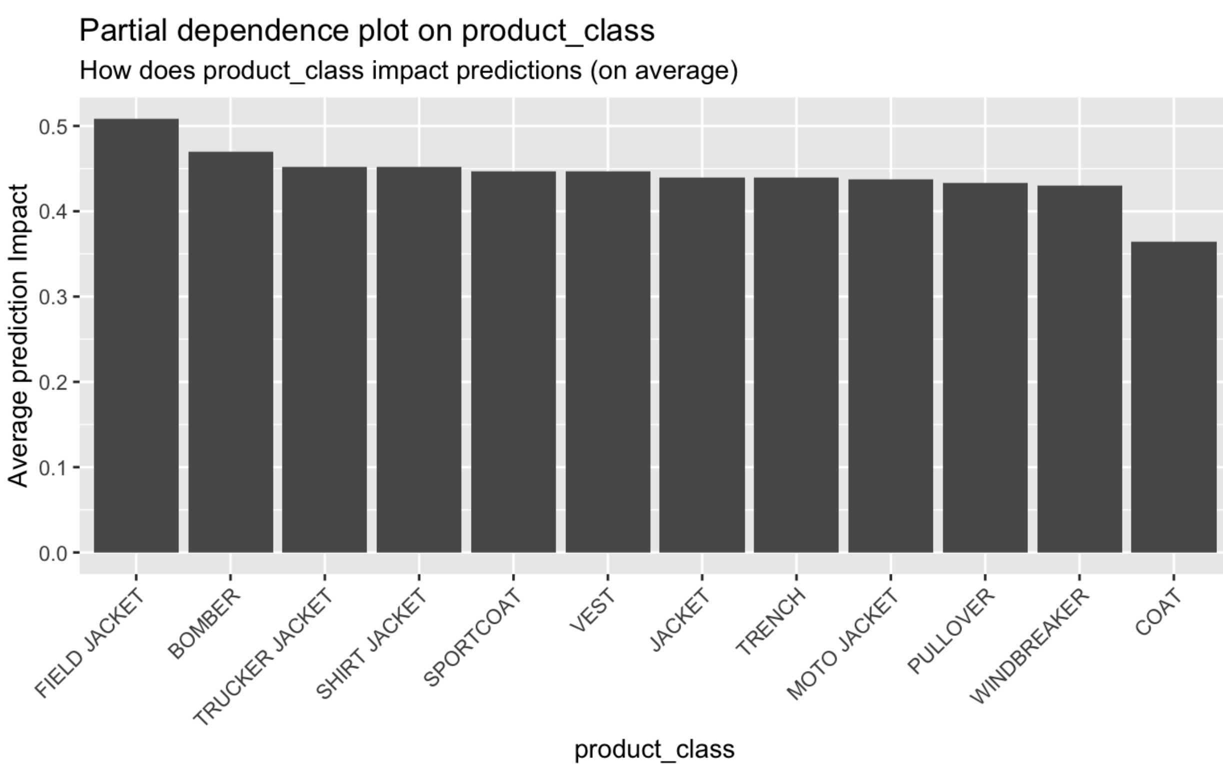

Partial dependence plot on fit
How does fit impact predictions (on average)
Average prediction Impact
0.0
0.1
0.2
0.3
0.4
0.5
NO FIT
STANDARD
CUSTOM SLIM
0
CLASSIC
fit


Partial dependence plot on super_color
How does super_color impact predictions (on average)
Average prediction Impact
0.0
0.2
0.4
BLACK
WHITE
'-1
NATURAL
GREY
YELLOW
RED
BROWN
GREEN
MULTI
NAVY
ORANGE
BLUE
super_color


Partial dependence plot on fiber_content
How does fiber_content impact predictions (on average)
Average prediction Impact
0.0
0.2
0.4
LEATHER/SU
POLYETHYLE
NYLON
POLYESTER
LINEN
WOOL
COTTON
fiber_content



Partial dependence plot on pricing
How does pricing impact predictions (on average)
Average prediction Impact
0.0
0.1
0.2
0.3
0.4
0.5
BETTER
LUXURY
0
GOOD
BEST
pricing



Partial dependence plot on product_class
How does product_class impact predictions (on average)
Average prediction Impact
0.0
0.1
0.2
0.3
0.4
0.5
FIELD JACKET
BOMBER
TRUCKER JACKET
SHIRT JACKET
SPORTCOAT
VEST
JACKET
TRENCH
MOTO JACKET
PULLOVER
WINDBREAKER
COAT
product_class

The above plots display the average probability of productivity of a specific level within an attribute while keeping all other factors constant. For instance, looking at the super color plot, we can observe that, on average, black men's outerwears have a >50% probability of achieving a global SKU score of 1, 2, 3, or 4 based on the model. In comparison, orange men's outerwears have a ~42% probability of being productive. Therefore, we can infer that black men's outerwears have a ~8% higher probability of being productive than orange men's outerwears on average.

Again, it is important to note that this is an aggregate view. There are many black men's outerwear that are not productive, just as there are many orange men's outerwears that are. This method examines the score assigned to each product within a category while holding every other attribute constant and takes an average of that score. It's particularly valuable in deciphering complex "black box" machine learning techniques, such as the XGBoost.

Growth Market: Women Outerwear

Used Variables

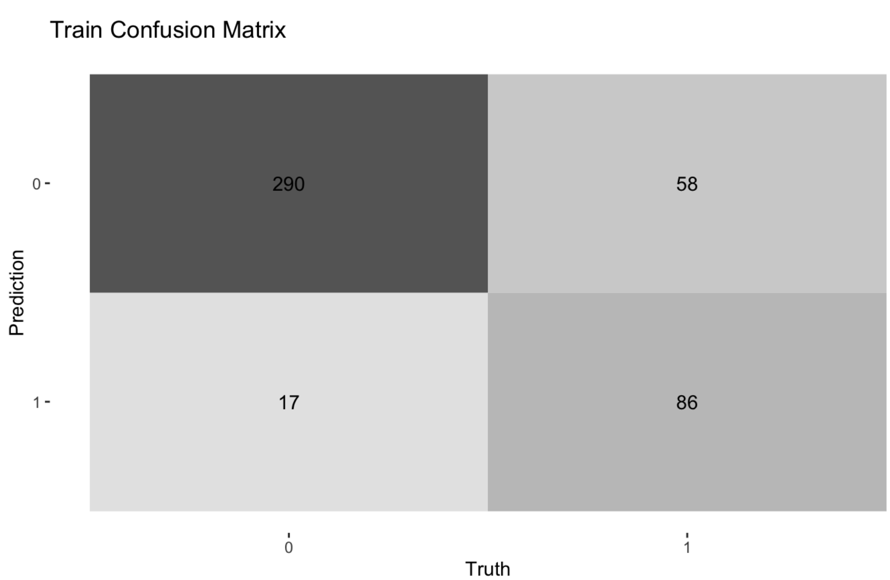
- **Fashion Degree:** seasonal, seasonal core, core
- **Fiber Content:** cowhide, acetate, walnut, cashmere, silk, leather, polyethylene, nylon, polyester, linen, wool, cotton
- **Global Plan L4:** outerwear
- **Fit:** active, no fit, standard, custom slim, classic, relaxed
- **Material Group:** wovens, sweaters, knits, skins
- **Logo:** big player, branded, label, monogram, no logo, novelty, other branding, rl (embroidery), small player
- **Merch Fabrication:** twill, poplin, chamray, herringbone, denim, ripstop
- **Pricing:** good, better, best, luxury
- **Style Pattern:** colorblock, non-printed pattern, novelty, plaid/check, print, solid, stripe
- **Product Class:** field jacket, vest, shirt jacket, bomber, blazer, windbreaker, moto jacket, poncho, pullover, trench, trucker jacket, coat
- **Neckline:** collar, crew neck, hoodie, mock neck, not applicable, other, polo knit collar, polo self-collar, spread collar, turtleneck, v neck, button down collar
- **Super Color**

Final Model

XGBoost trees = 11, learn rate = 0.04380312

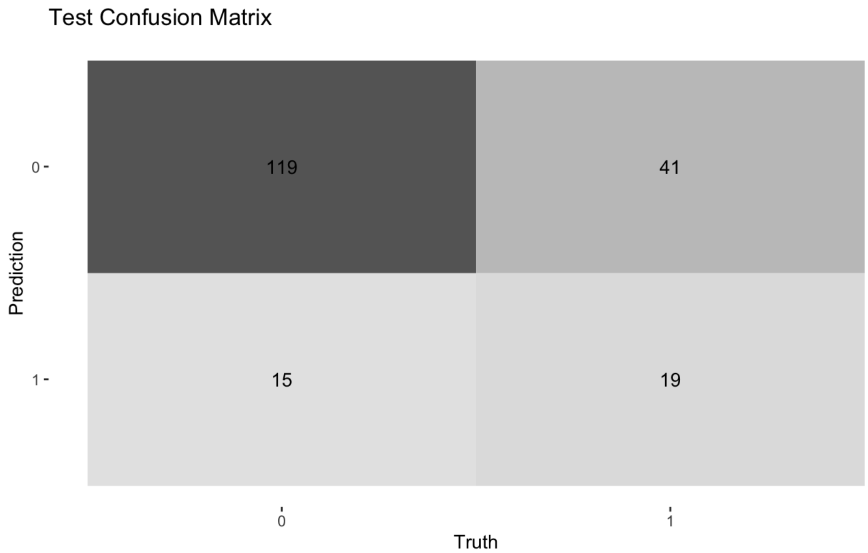
Training Set Metrics & Confusion Matrix:

.estimator <chr>	part <chr>	accuracy <dbl>	kap <dbl>	mn_log_loss <dbl>	roc_auc <dbl>
binary	training	0.8337029	0.5861525	0.5364732	0.9381447

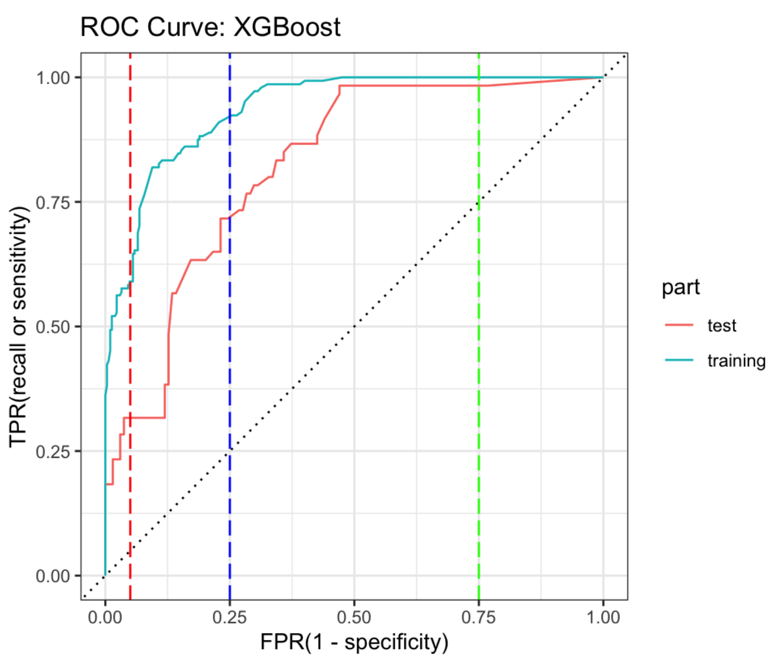


Test Set Metrics & Confusion Matrix:

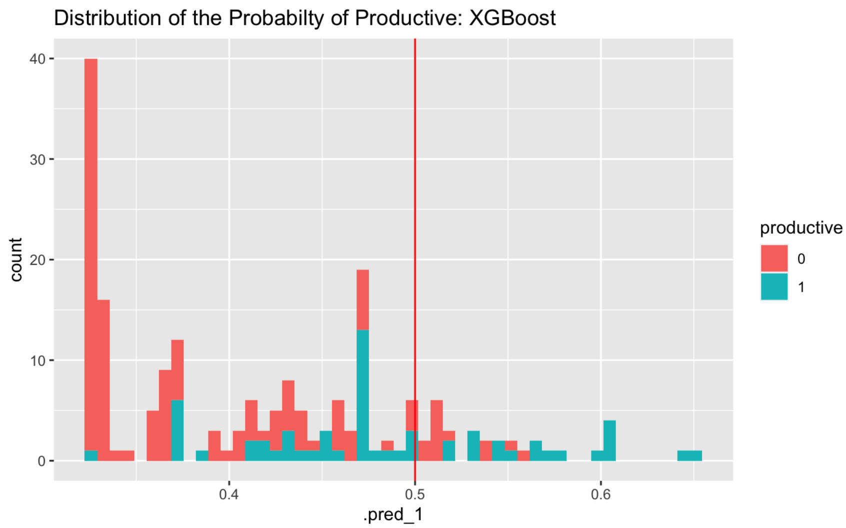
.estimator <chr>	part <chr>	accuracy <dbl>	kap <dbl>	mn_log_loss <dbl>	roc_auc <dbl>
binary	testing	0.7113402	0.2325516	0.5747873	0.8215796



ROC Curve (False Positive Rate on X Axis, True Positive Rate on Y Axis):

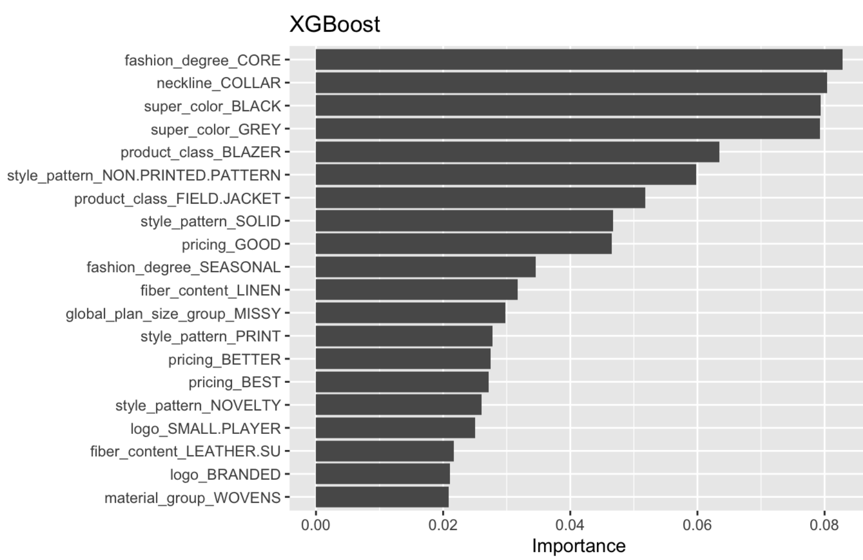


Distribution of Productive Probabilities:



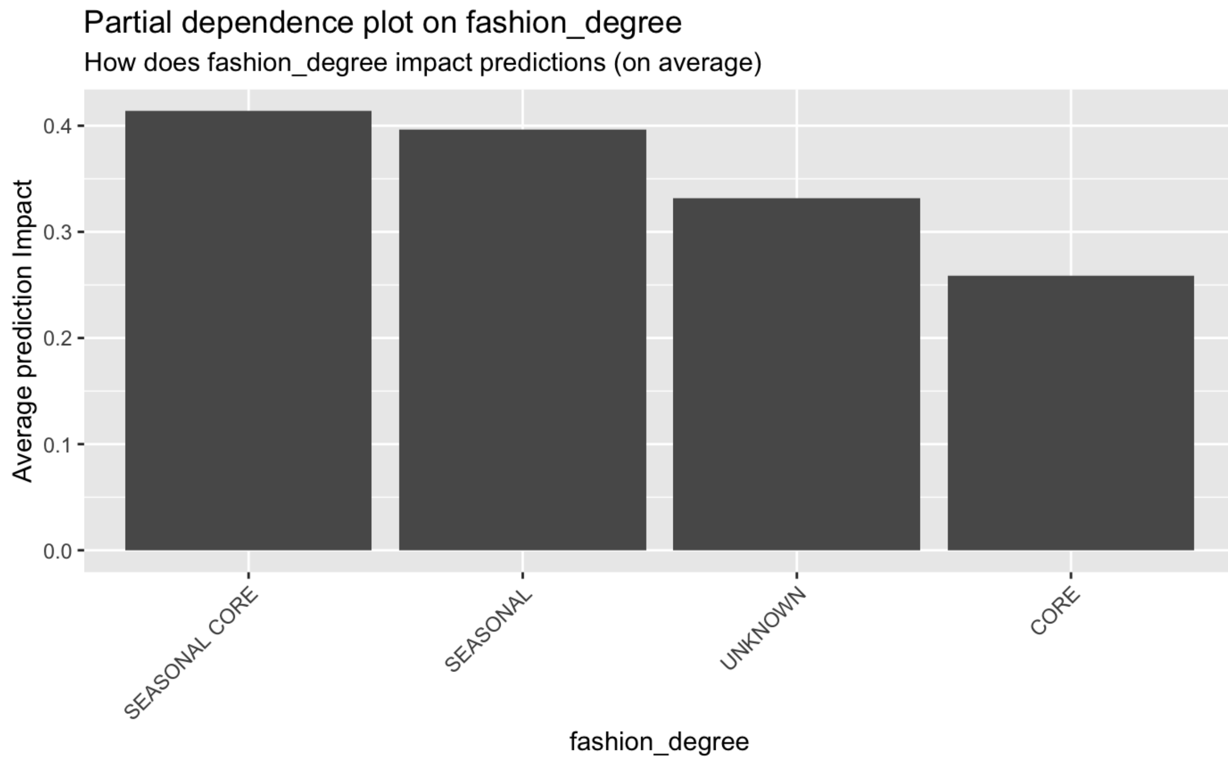
- pred_1 is the probability of productivity while the fill indicates the score of the product (1 for productive, 0 for unproductive)

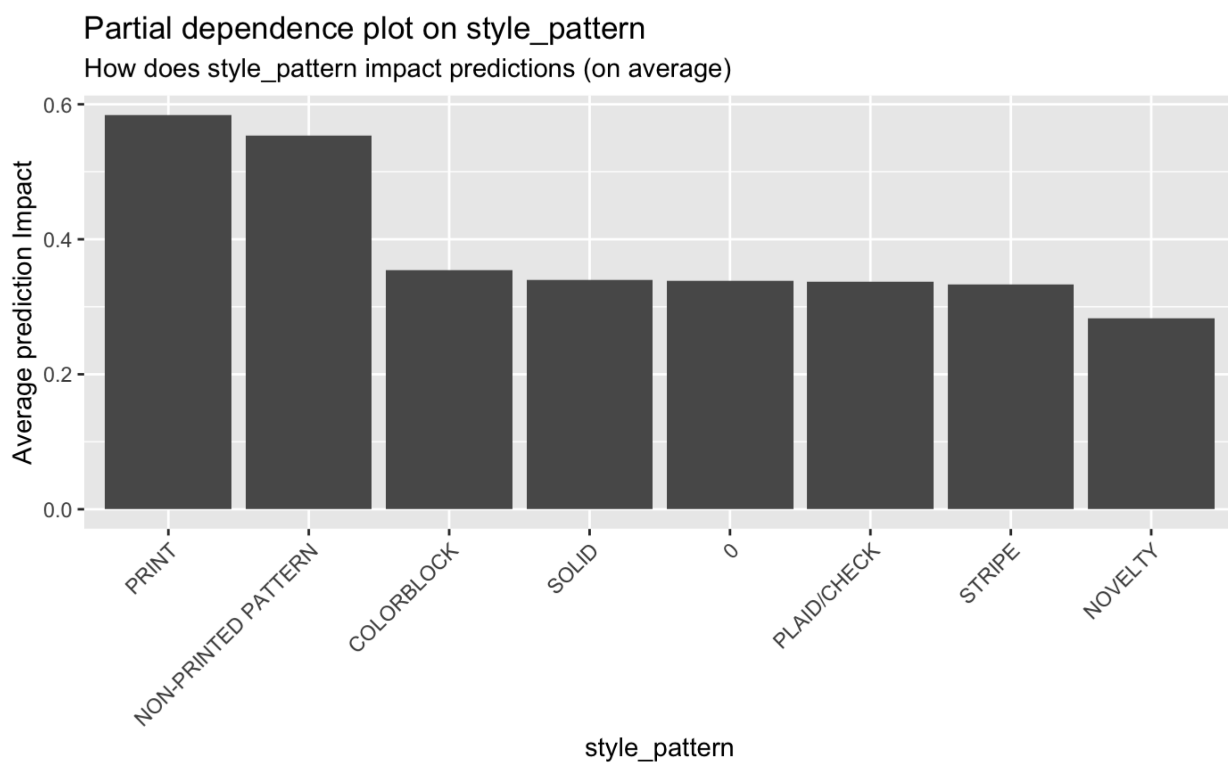
Variable Importance:

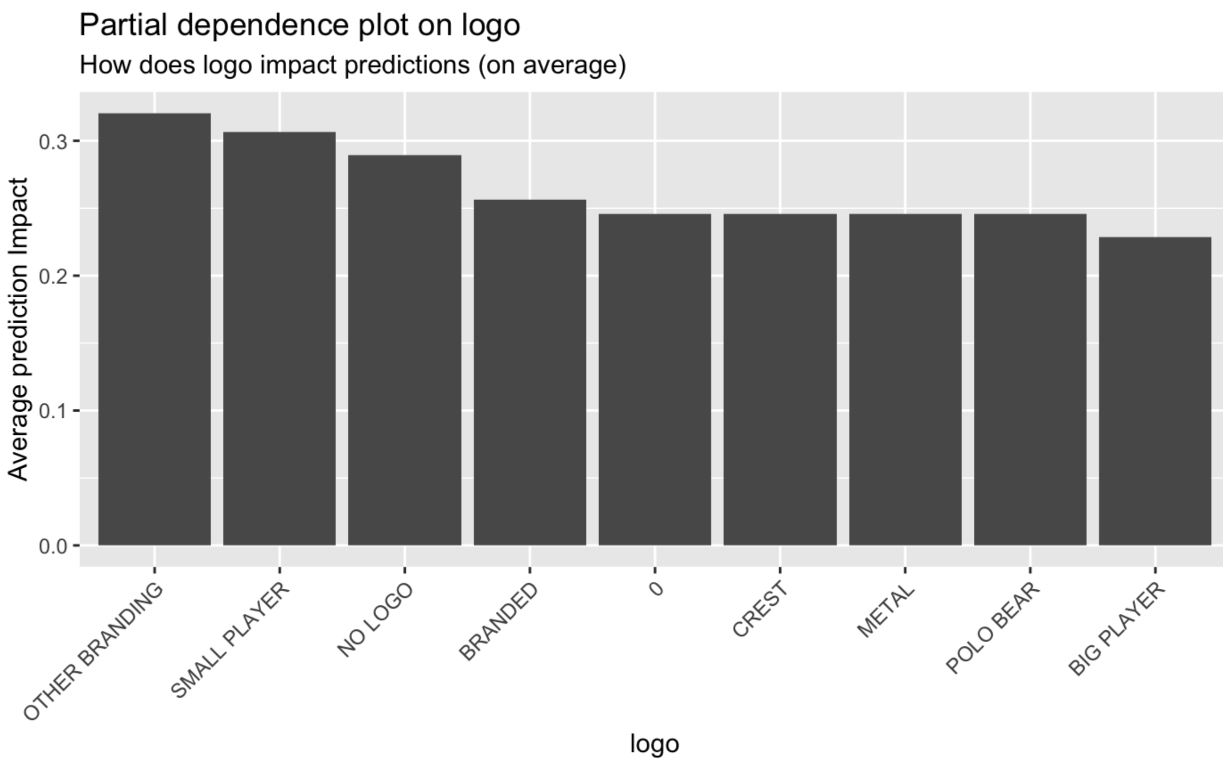


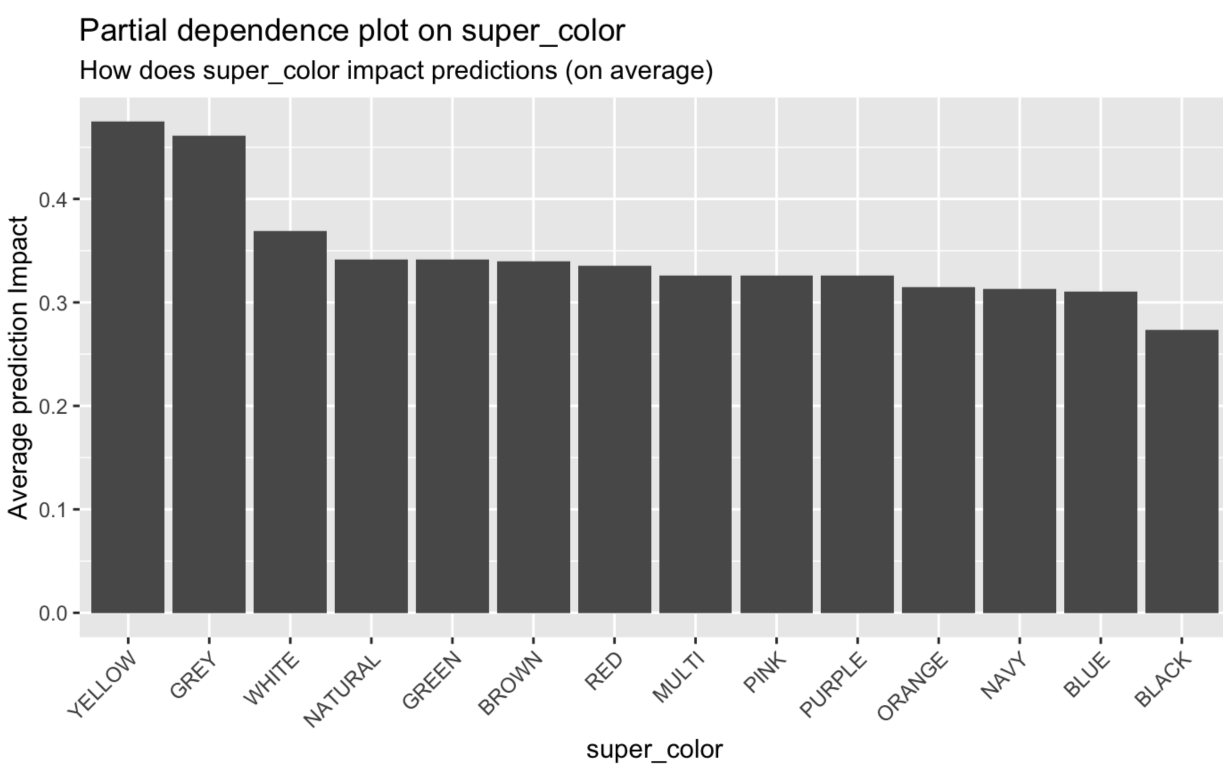
The chart above illustrates the variable importance in determining whether a unique SKU is productive or not. It highlights the attributes that have the highest correlation with productivity. According to the graph, women's outerwears are highly influenced by core trends, with collar, black, and grey being the most productive features. Additionally, blazer, non print pattern, or field jacket designs are generally more favorable in terms of productivity.

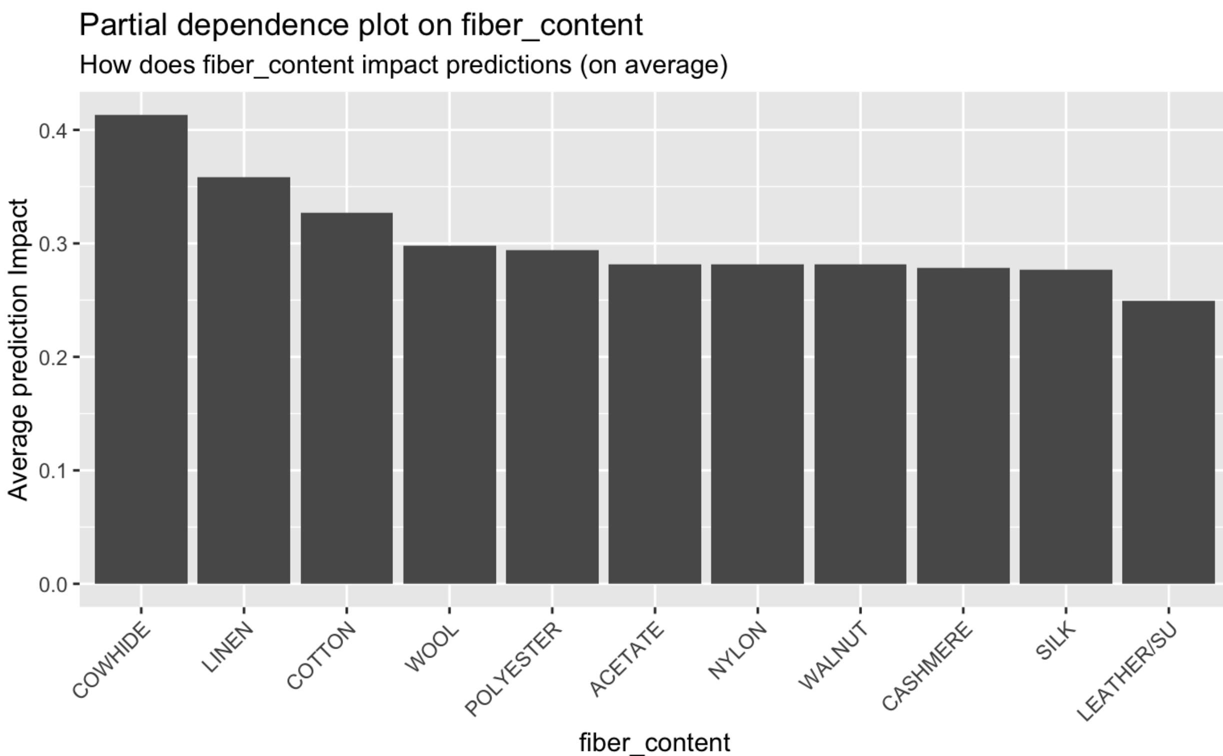
Partial Dependency Plots:

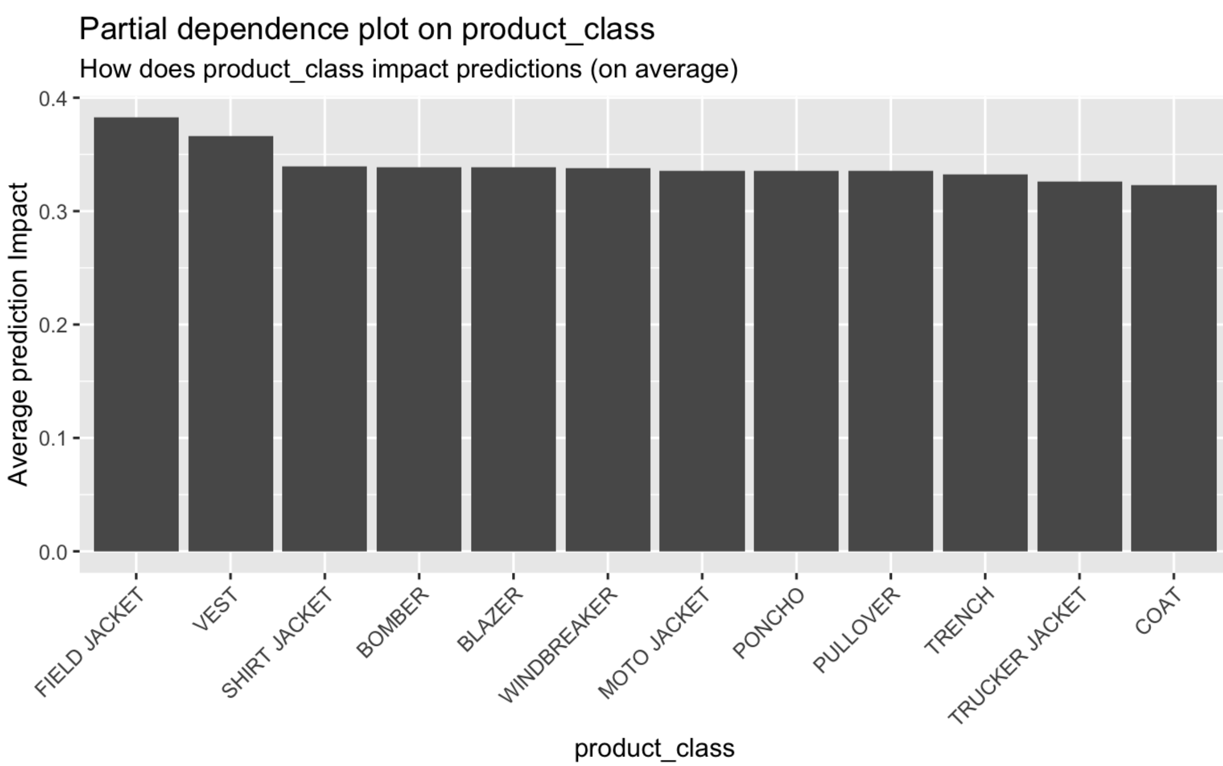


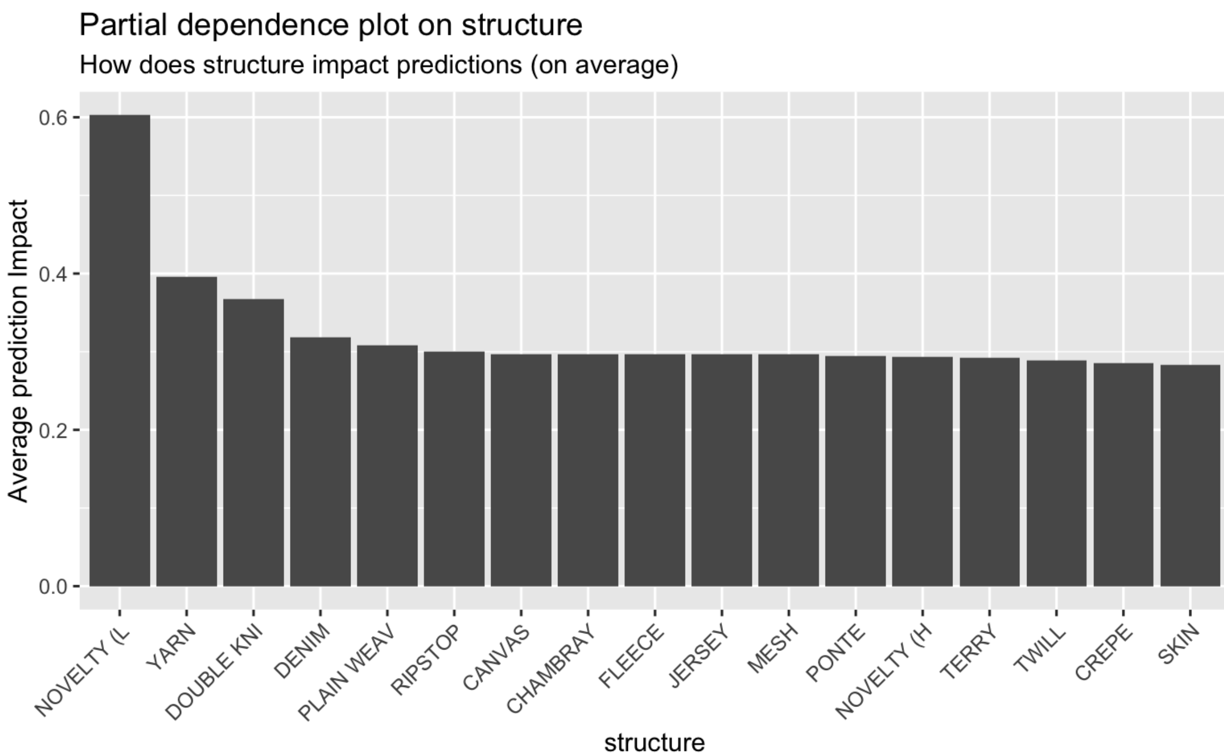


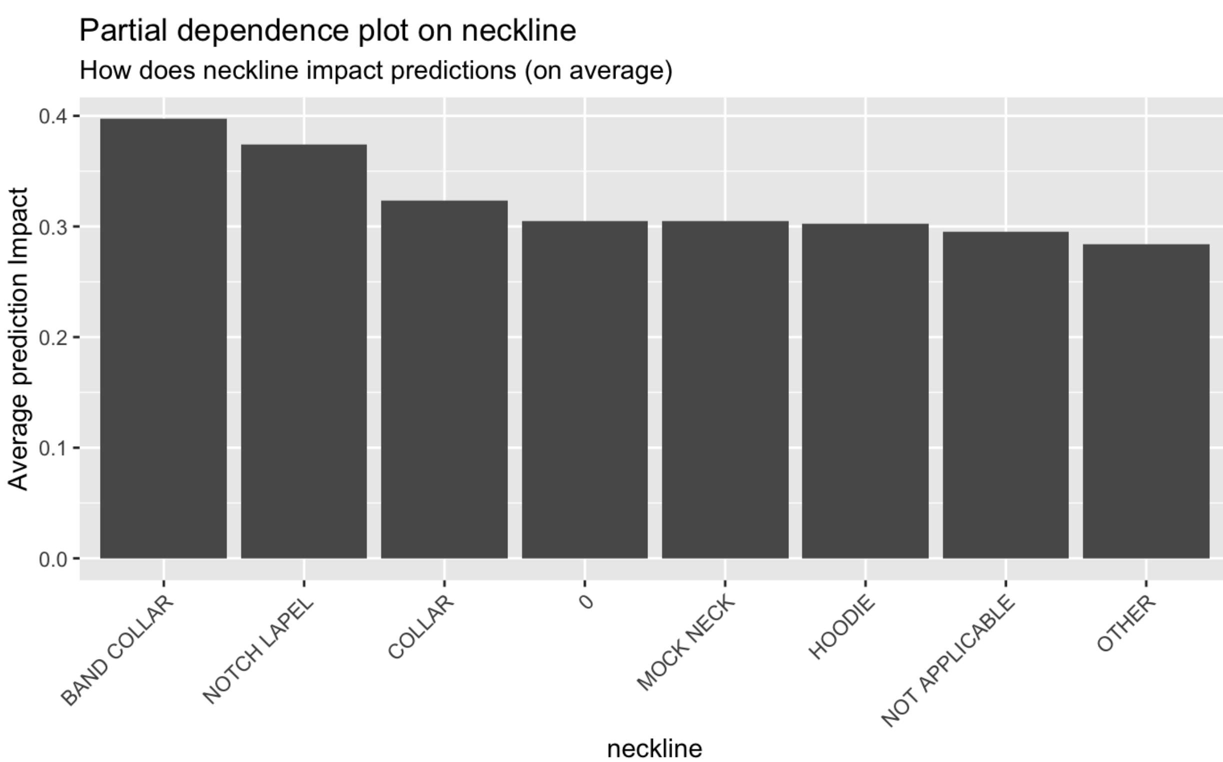

Partial dependence plot on logo
How does logo impact predictions (on average)
Average prediction Impact
0.0
0.1
0.2
0.3
OTHER BRANDING
SMALL PLAYER
NO LOGO
BRANDED
0
CREST
METAL
POLO BEAR
BIG PLAYER
logo


Partial dependence plot on super_color
How does super_color impact predictions (on average)
Average prediction Impact
0.0
0.1
0.2
0.3
0.4
YELLOW
GREY
WHITE
NATURAL
GREEN
BROWN
RED
MULTI
PINK
PURPLE
ORANGE
NAVY
BLUE
BLACK
super_color


Partial dependence plot on fiber_content
How does fiber_content impact predictions (on average)
Average prediction Impact
0.0
0.1
0.2
0.3
0.4
COWHIDE
LINEN
COTTON
WOOL
POLYESTER
ACETATE
NYLON
WALNUT
CASHMERE
SILK
LEATHER/SU
fiber_content


Partial dependence plot on product_class
How does product_class impact predictions (on average)
Average prediction Impact
0.0
0.1
0.2
0.3
0.4
FIELD JACKET
VEST
SHIRT JACKET
BOMBER
BLAZER
WINDBREAKER
MOTO JACKET
PONCHO
PULLOVER
TRENCH
TRUCKER JACKET
COAT
product_class


Partial dependence plot on structure
How does structure impact predictions (on average)
Average prediction Impact
0.0
0.2
0.4
0.6
NOVELTY (L
YARN
DOUBLE KNI
DENIM
PLAIN WEAV
RIPSTOP
CANVAS
CHAMBRAY
FLEECE
JERSEY
MESH
PONTE
NOVELTY (H
TERRY
TWILL
CREPE
SKIN
structure


Partial dependence plot on neckline
How does neckline impact predictions (on average)
Average prediction Impact
0.0
0.1
0.2
0.3
0.4
BAND COLLAR
NOTCH LAPEL
COLLAR
0
MOCK NECK
HOODIE
NOT APPLICABLE
OTHER
neckline

The above plots display the average probability of productivity of a specific level within an attribute while keeping all other factors constant. For instance, looking at the super color plot, we can observe that, on average, grey women's outerwears have a >50% probability of achieving a global SKU score of 1, 2, 3, or 4 based on the model. In comparison, black women's outerwears have a <30% probability of being productive. Therefore, we can infer that grey women's outerwears have a >20% higher probability of being productive than black women's outerwears on average.

Again, it is important to note that this is an aggregate view. There are many grey women's outerwear that are not productive, just as there are many black women's outerwears that are. This method examines the score assigned to each product within a category while holding every other attribute constant and takes an average of that score. It's particularly valuable in deciphering complex "black box" machine learning techniques, such as the XGBoost.