# Estimating Client Needs Business Case 2

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## Goal: Recommendation System

We intend to estimate some investments needs for these customers using Data Science techniques.

#### Data:

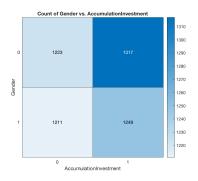
#### Needs:

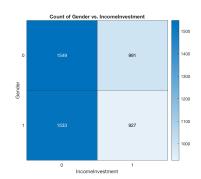
```
ID Age Gender FamilyMembers FinancialEducation RiskPropensity
Income Wealth IncomeInvestment AccumulationInvestment
```

#### Products:

IDProduct Type Risk

# No significant sex difference





#### Data Transformation

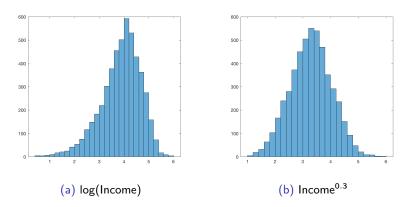
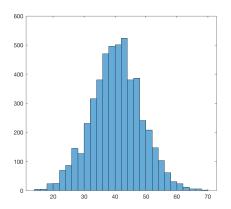


Figure: Comparison of transformations, we'll go with the second.

#### Data Transformation

Using a boxcox transformation,  $NewAge = (OldAge^{0.9} - 1)/0.9$ .



### Data Transformation

 $\label{eq:NewFinancialEducation} NewFinancialEducation = OldFinancialEducation^{0.8} \\ NewRiskPropensity = OldRiskPropensity^{0.65} \\ NewIncome = OldIncome^{0.3} \\$ 

#### Cross validation

```
nObs = size(Data, 1);
rng(10)
idxPermutation = randperm(nObs);
X = X(idxPermutation,:); % random permutation
train = 0.75 ;
cross = 0 ;

nObsTrain = round(train*nObs);
nObsCross = round(cross*nObs);

XTrain = X(1:nObsTrain,:);
XCross = X((nObsTrain+1):(nObsTrain+nObsCross), :);
XTest = X(nObsTrain+1+nObsCross:end,:);
```

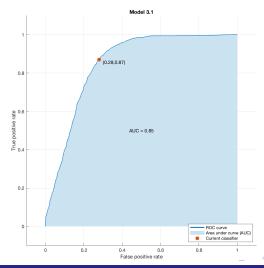
# Added Y permutation equal to X

```
YInc = Data.IncomeInvestment:
YInc = YInc(idxPermutation):
vInvIncTrain = YInc(1:nObsTrain);
vInvIncCross = YInc((nObsTrain+1):(nObsTrain+nObsCross));
vInvIncTest = YInc(nObsTrain+nObsCross+1:end);
YAcc = Data.AccumulationInvestment:
YAcc = YAcc(idxPermutation):
vInvAccTrain = YAcc(1:nObsTrain);
vInvAccCross = YAcc((nObsTrain+1):(nObsTrain+nObsCross));
vInvAccTest = YAcc(nObsTrain+nObsCross+1:end):
varNames = {'Age', 'Gender', 'Family', 'FinEdu', 'Risk', 'Income', 'Wealth'};
XTrainTable=table(XTrain(:.1), XTrain(:.2), XTrain(:.3), XTrain(:.4),
XTrain(:.5). XTrain(:.6).XTrain(:.7). 'VariableNames'.varNames):
XTestTable=table(XTest(:,1), XTest(:,2), XTest(:,3), XTest(:,4),
XTest(:.5). XTest(:.6).XTest(:.7). 'VariableNames'.varNames):
```

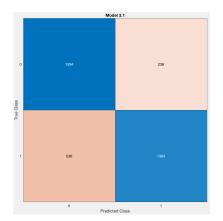
# Classification Learner: model training

1.5	1.4 KNN Last change: Fine KNN	Accuracy: 65.7% 7/7 features
Last change: Coarse KNN 7/7 features  1.7    KNN Accuracy: 69.8%  Last change: Cosine KNN 7/7 features  1.8    KNN Accuracy: 69.1%  Last change: Cubic KNN 7/7 features  1.9    KNN Accuracy: 69.7%  Last change: Weighted KNN 7/7 features  2    Ensemble Accuracy: 79.4%  Last change: Boosted Trees 7/7 features  3.1    Ensemble Accuracy: 79.4%  Last change: Boosted Trees 7/7 features  3.2    Ensemble Accuracy: 76.6%  Last change: Boosted Trees 7/7 features  3.3    Ensemble Accuracy: 76.6%  Last change: Subspace Discrimin 7/7 features  3.4    Ensemble Accuracy: 70.0%  Last change: Subspace KNN 7/7 features  3.5    Ensemble Accuracy: 70.0%		
Last change: Cosine KNN 7/7 features  1.8 KNN Accuracy: 69.1%  1.9 KNN Accuracy: 69.7% Last change: Weighted KNN 7/7 features  2 Ensemble Accuracy: 79.4% Last change: Boosted Trees 7/7 features  3.1 Ensemble Accuracy: 79.4% Last change: Boosted Trees 7/7 features  3.2 Ensemble Accuracy: 76.6% Last change: Bagged Trees 7/7 features  3.3 Ensemble Accuracy: 76.6% Last change: Subspace Discrimin 7/7 features  3.4 Ensemble Accuracy: 70.0% Last change: Subspace KNN 7/7 features  3.5 Ensemble Accuracy: 70.0% Last change: Subspace KNN 7/7 features  3.5 Ensemble Accuracy: 70.0%  3.6 Ensemble Accuracy: 70.0%  3.7 Features  3.8 Ensemble Accuracy: 70.0%  Accuracy: 70.0%  Accuracy: 70.0%  Accuracy: 70.0%  Accuracy: 70.0%  Accuracy: 70.0%  Accuracy: 75.0%		
Last change: Cubic KNN 7/7 features  1.9		
Last change: Weighted KNN 7/7 features  2		
Last change: Boosted Trees  3.1		
Last change: Boosted Trees  3.2 © Ensemble Accuracy: 76.6% Last change: Bagged Trees  3.3 © Ensemble Accuracy: 62.9% Last change: Subspace Discrimin 7/7 features  3.4 © Ensemble Accuracy: 70.0% Last change: Subspace KNN 7/7 features  3.5 © Ensemble Accuracy: 70.0%  3.6 © Ensemble Accuracy: 75.0%	- 1/4	,
Last change: Bagged Trees 7/7 features 3.3 Ensemble Accuracy: 62.9% Last change: Subspace Discrimin 7/7 features 3.4 Ensemble Accuracy: 70.0% Last change: Subspace KNN 7/7 features 3.5 Ensemble Accuracy: 75.0%		
Last change: Subspace Discrimin 7/7 features  3.4 ☆ Ensemble Accuracy: 70.0% Last change: Subspace KNN 7/7 features  3.5 ☆ Ensemble Accuracy: 75.0%		
Last change: Subspace KNN 7/7 features  3.5  Ensemble Accuracy: 75.0%		
Last change. ROSBOOSted Trees /// readures	5p	7/7 features

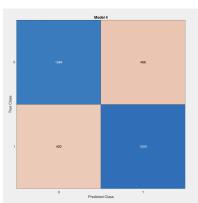
## Classification Learner: Boosted Tree ROC



## Classification Learner: Boosted Tree confusion matrix



(a) Confusion matrix.



(b) Penalized confusion matrix.

## Reducing data

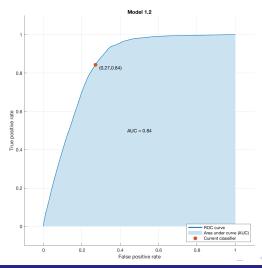
We remove Gender, Risk and FamilySize and added IncomeWealthRatio = Income / Wealth.

```
Xsmall = [rescale(IncomeWealthRatio) rescale(pAge) rescale(pFin) rescale(pIncome) rescale(pWealth)];
Xsmall = Xsmall(idxPermutation,:);
XsmallTrain = Xsmall(1:nObsTrain,:);
XsmallTest = Xsmall(nObsTrain+1:end,:);
XsmallTrainTable=table(XsmallTrain(:,1), XsmallTrain(:,2), XsmallTrain(:,3),
XsmallTrain(:,4), XsmallTrain(:,5), 'VariableNames',xnames);
```

## Classification Learner: model training

1.1 A Ensemble Last change: Boosted Trees	Accuracy: 78.3% 5/5 features
1.2 🖒 Ensemble [ Last change: Bagged Trees	Accuracy: <b>78.5%</b> 5/5 features
1.3 🏠 Ensemble Last change: Subspace Discrim	Accuracy: 65.9% in 5/5 features
1.4 🏠 Ensemble Last change: Subspace KNN	Accuracy: 73.4% 5/5 features
1.5 🏠 Ensemble Last change: RUSBoosted Trees	Accuracy: 76.3% 5/5 features
2.1 🏠 Tree Last change: Fine Tree	Accuracy: 78.0% 5/5 features
2.2 🏠 Tree Last change: Medium Tree	Accuracy: 76.1% 5/5 features
2.3 Tree Last change: Coarse Tree	Accuracy: 68.0% 5/5 features
2.4 KNN Last change: Fine KNN	Accuracy: 70.5% 5/5 features

## Classification Learner: Bagged Tree ROC



## Recommending products

Using MATLAB's automatic hyperparameters optimization we decide to use the Bagged Tree model after evaluating 30 alternatives.

## Product recommendation based on Risk Propensity



- more data cleaning to improve model accuracy;
- better data visualization for product recommendation.