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:

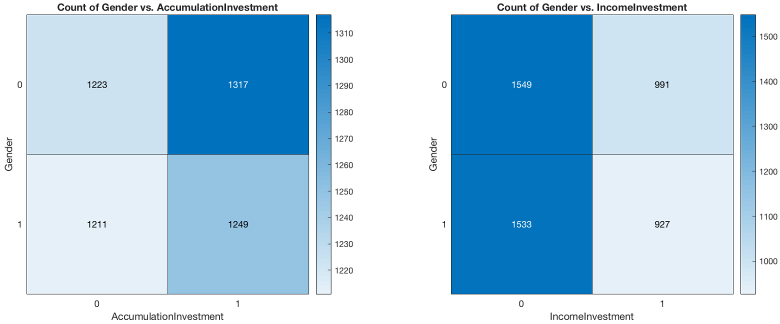
Needs:

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

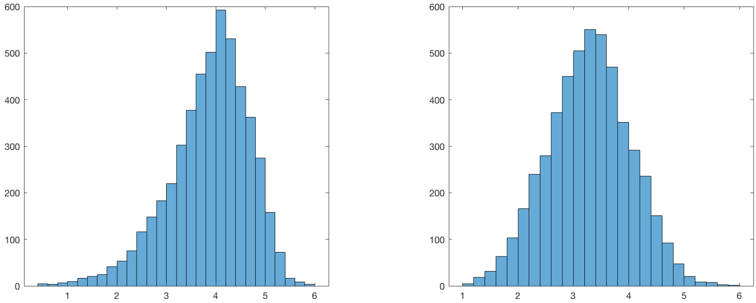
Products:

`IDProduct` `Type` `Risk`

No significant sex difference



Data Transformation

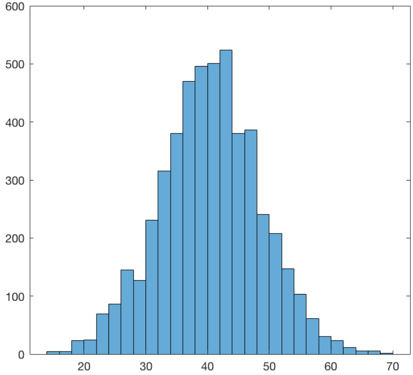


(a) log(Income) (b) Income$^{0.3}$

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

Data Transformation

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



Data Transformation

$$\text{NewFinancialEducation} = \text{OldFinancialEducation}^{0.8}$$
$$\text{NewRiskPropensity} = \text{OldRiskPropensity}^{0.65}$$
$$\text{NewIncome} = \text{OldIncome}^{0.3}$$

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,:);
```

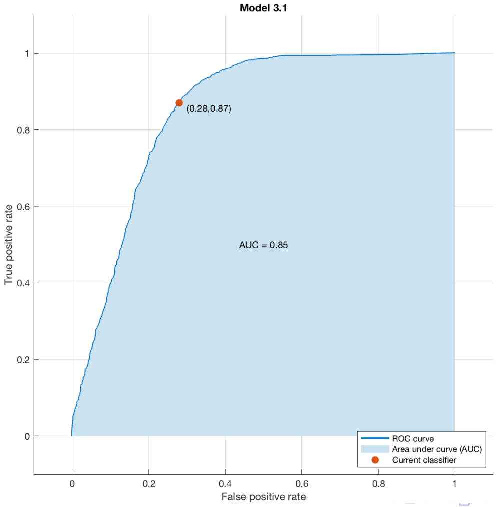
Added Y permutation equal to X

```
YInc = Data.IncomeInvestment;
YInc = YInc(idxPermutation);

yInvIncTrain = YInc(1:nObsTrain);
yInvIncCross = YInc((nObsTrain+1):(nObsTrain+nObsCross));
yInvIncTest = YInc(nObsTrain+nObsCross+1:end);

YAcc = Data.AccumulationInvestment;
YAcc = YAcc(idxPermutation);

yInvAccTrain = YAcc(1:nObsTrain);
yInvAccCross = YAcc((nObsTrain+1):(nObsTrain+nObsCross));
yInvAccTest = 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);
```

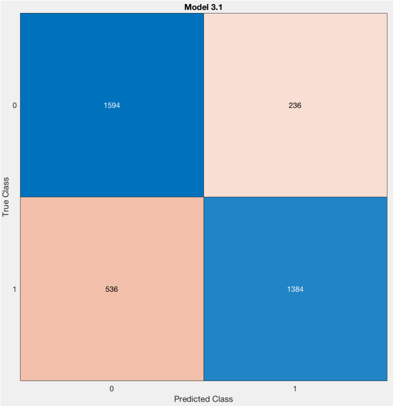
Classification Learner: model training

Model	Type	Last change	Accuracy	Features
1.4	KNN	Fine KNN	65.7%	7/7 features
1.5	KNN	Medium KNN	69.8%	7/7 features
1.6	KNN	Coarse KNN	68.9%	7/7 features
1.7	KNN	Cosine KNN	69.8%	7/7 features
1.8	KNN	Cubic KNN	69.1%	7/7 features
1.9	KNN	Weighted KNN	69.7%	7/7 features
2	Ensemble	Boosted Trees	**79.4%**	7/7 features
3.1	Ensemble	Boosted Trees	**79.4%**	7/7 features
3.2	Ensemble	Bagged Trees	76.6%	7/7 features
3.3	Ensemble	Subspace Discrimin...	62.9%	7/7 features
3.4	Ensemble	Subspace KNN	70.0%	7/7 features
3.5	Ensemble	RUSBoosted Trees	75.0%	7/7 features

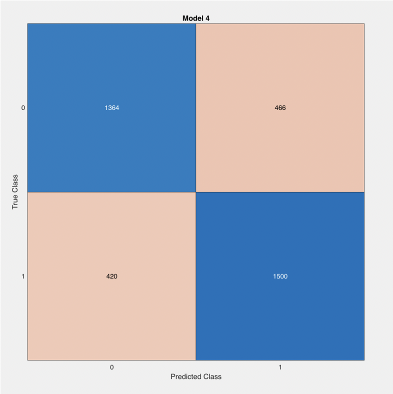
Classification Learner: Boosted Tree ROC



Classification Learner: Boosted Tree confusion matrix



(a) Confusion matrix.



(b) Penalized confusion matrix.

Reducing data

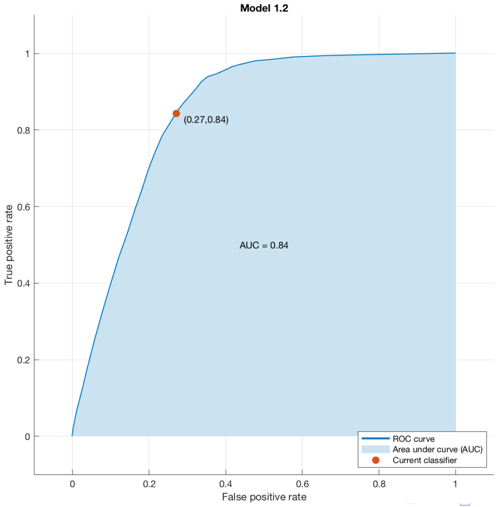
We remove `Gender` and `FamilySize`

```
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

Model	Type	Last change	Accuracy	Features
1.1	Ensemble	Boosted Trees	78.3%	5/5 features
1.2	Ensemble	Bagged Trees	**78.5%**	5/5 features
1.3	Ensemble	Subspace Discrimin...	65.9%	5/5 features
1.4	Ensemble	Subspace KNN	73.4%	5/5 features
1.5	Ensemble	RUSBoosted Trees	76.3%	5/5 features
2.1	Tree	Fine Tree	78.0%	5/5 features
2.2	Tree	Medium Tree	76.1%	5/5 features
2.3	Tree	Coarse Tree	68.0%	5/5 features
2.4	KNN	Fine KNN	70.5%	5/5 features

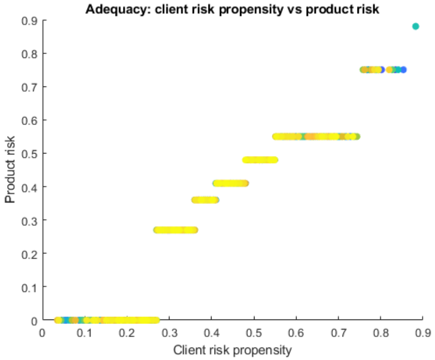
Classification Learner: Bagged Tree ROC



Recommending products

Using Bayesian 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.