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Modern Model, Wise Solution

--- predictive model based solutions for Altra to fight against insurance fraud

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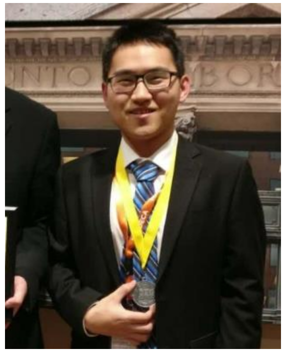
Our Team

Iris Guo
Research Analyst

Experience in conducting industry standard research in the P&C market.



Bill Zhuo
Quantitative Specialist

Experience in quantitative financial modelling and machine learning algorithm implementations. Technical data support for the team.

Cody Xu
Risk Analyst

Experience in Enterprise Risk Management and Insurance Risk Mitigation Strategies

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Product and Strategy Consultant

Experience in P&C insurance pricing and reserve analysis. Business strategy consulting support for the team.

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Background

Background

Motivation:

- **10%** of all claims paid by P&C insurer are fraudulent
  → high frequency of fraud

- **5 - 15%** of premiums goes toward covering undetected fraudulent claims
  → tackling fraud lead to savings to customers

- **68%** of people believed the root cause for fraud is lack of monitoring systems
  → our solution of data analysis

Company selection:

- Auto insurance fraud is estimated to cost taxpayers **$1.6 billion** annually

- We chose Altra because of the high frequency of fraud and the large amount of fraud in P&C

- With over **$2 billion** in auto book, Altra Insurance is a large P&C insurance company that has three main auto coverages - third party liability (TPL), collision, and comprehensive car insurance. To recover their financial loss from fraudulent claims, they need to restructure their products and find an alternate solution to increasing premiums.

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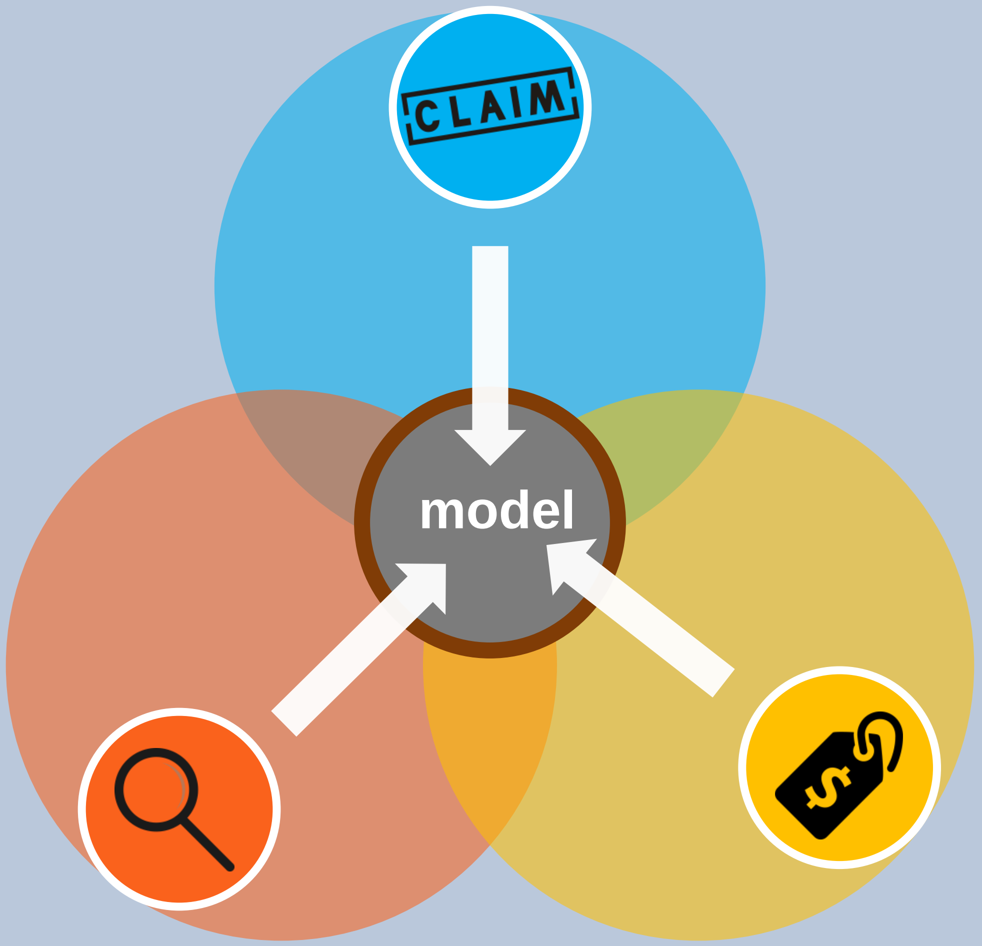
Solution Outline

03 claim

Be careful when giving out the money.

02 underwriting

Be wise when writing policies.

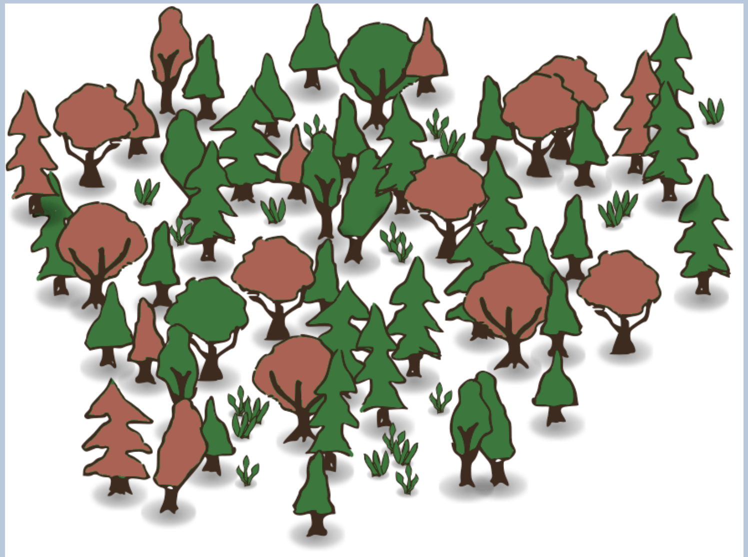


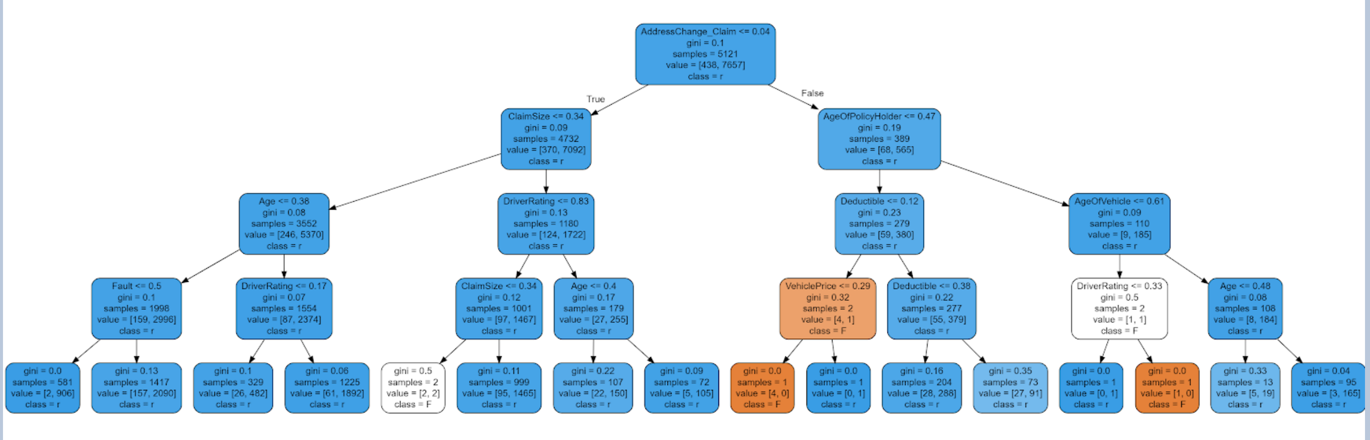
01 pricing

Be a strategic thinker when making rules for the game.

Predictive Model

Predictive Model: Balanced Random Forest





Model Selection:

1. Unsupervised Learning for Anomaly detection

2. Fit for imbalanced target set by **oversampling on the minority class**

Non-fraud	Fraud
1	1.75

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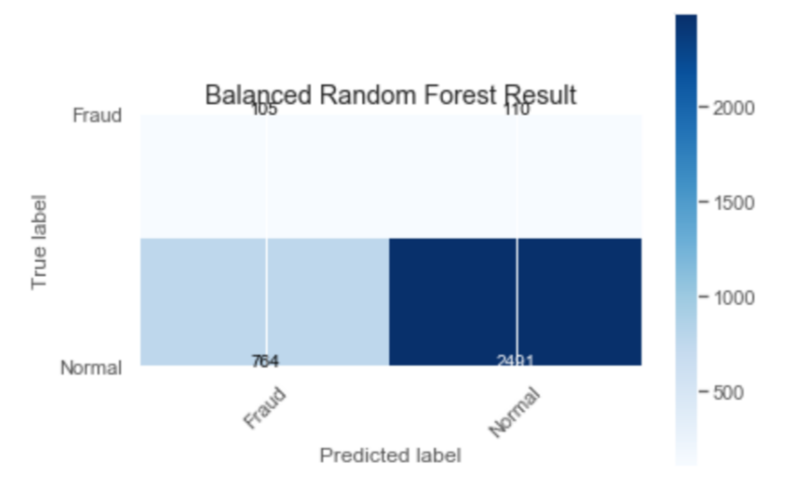
Model performance and Predictive Analytic

```
              precision    recall  f1-score   support

          -1       0.12      0.49      0.19       215
           1       0.96      0.77      0.85      3255

   micro avg       0.75      0.75      0.75      3470
   macro avg       0.54      0.63      0.52      3470
weighted avg       0.91      0.75      0.81      3470

Confusion matrix, without normalization
[[ 105  110]
 [ 764 2491]]
Accuracy: 0.7481268011527378
```



1. Reasonable accuracy with high recall rate
2. Focus on anomaly detection
3. Highest AUC out of all models
4. Desirable AUCPR

Predictive Model

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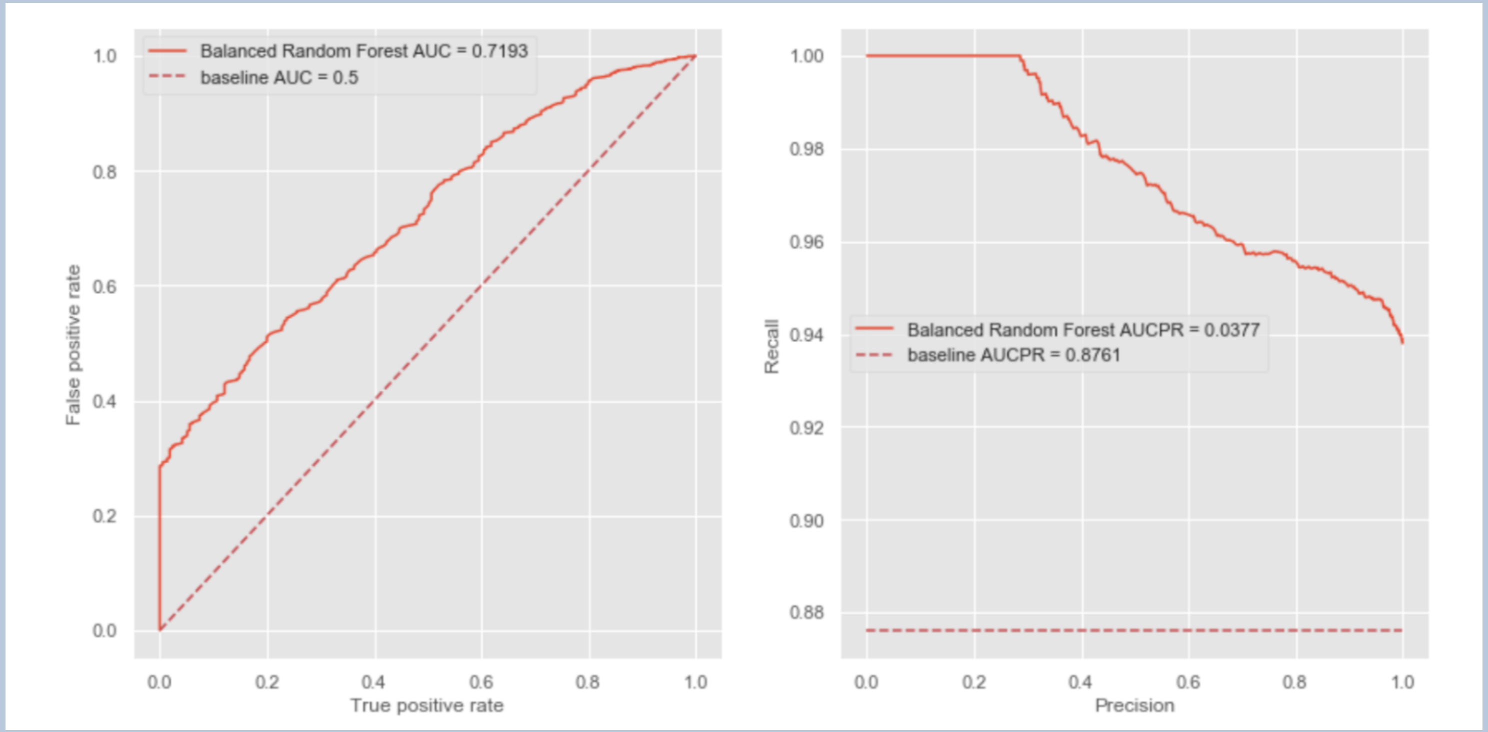

High AUC as an indicator of reliable overall model performance (0.7193)

Low AUCPR as an indicator of reliable anomaly detection performance (0.0377)

Classification Probability Score

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Probability Score: given by the balanced random forest classifier evaluated at each claim

*Pre-claim Probability Score

Probability Score (P)	Fraud Claim Amount (>=P)	Total Claim Amount (>=P)	Fraud Claim Proportion (%)
0.572	513	2191	23.4%
0.709	342	819	41.8%
0.788	169	308	54.9%

*Exclude Claim Size and Fault

Post-claim Probability Score

Probability Score (P)	Fraud Claim Amount (>=P)	Total Claim Amount (>=P)	Fraud Claim Proportion (%)
0.678	510	802	63.6%
0.744	333	393	84.7%
0.834	168	181	92.8%

Fraud Investigation

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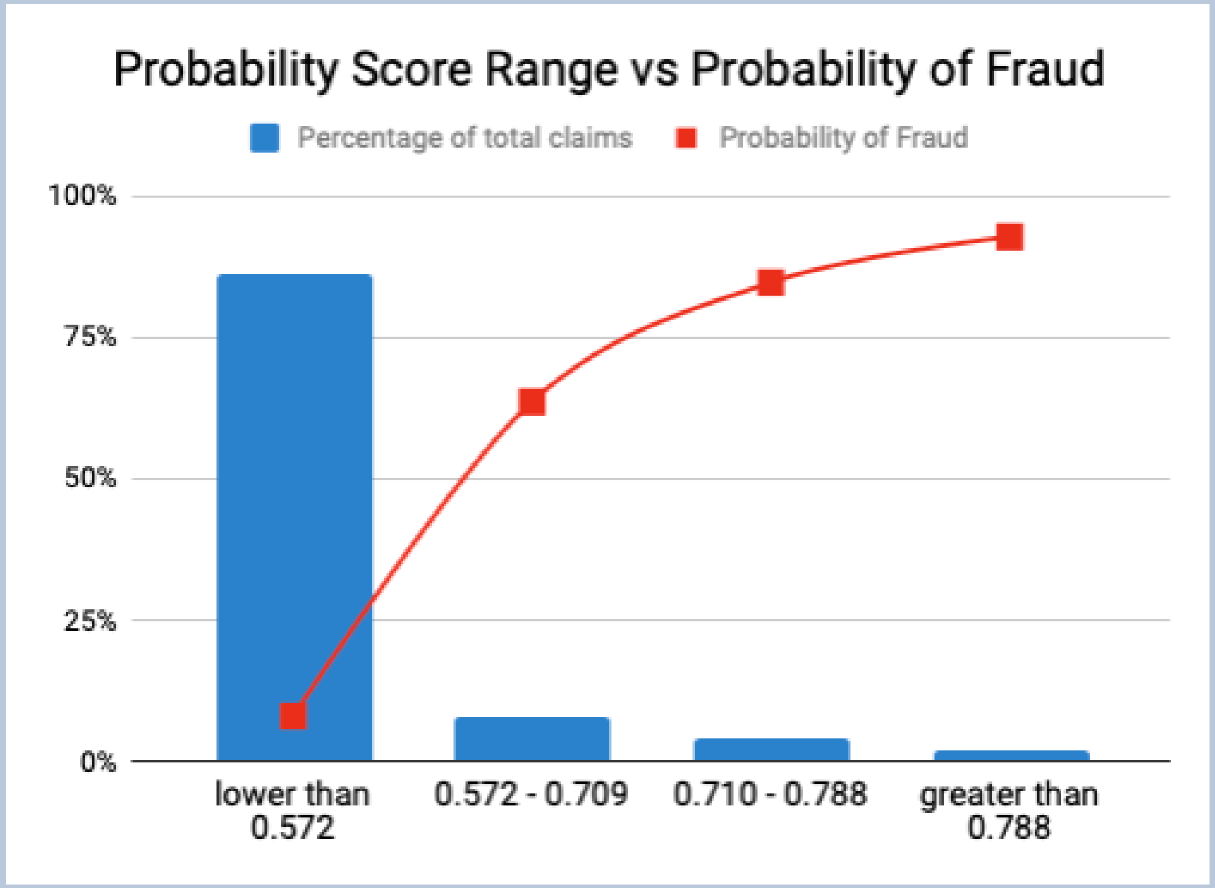
Top **14%** of claims includes **75%** of fraud.

More than **87%** of the claims in the top two probability score ranges are fraudulent.



Fraud Risk Management

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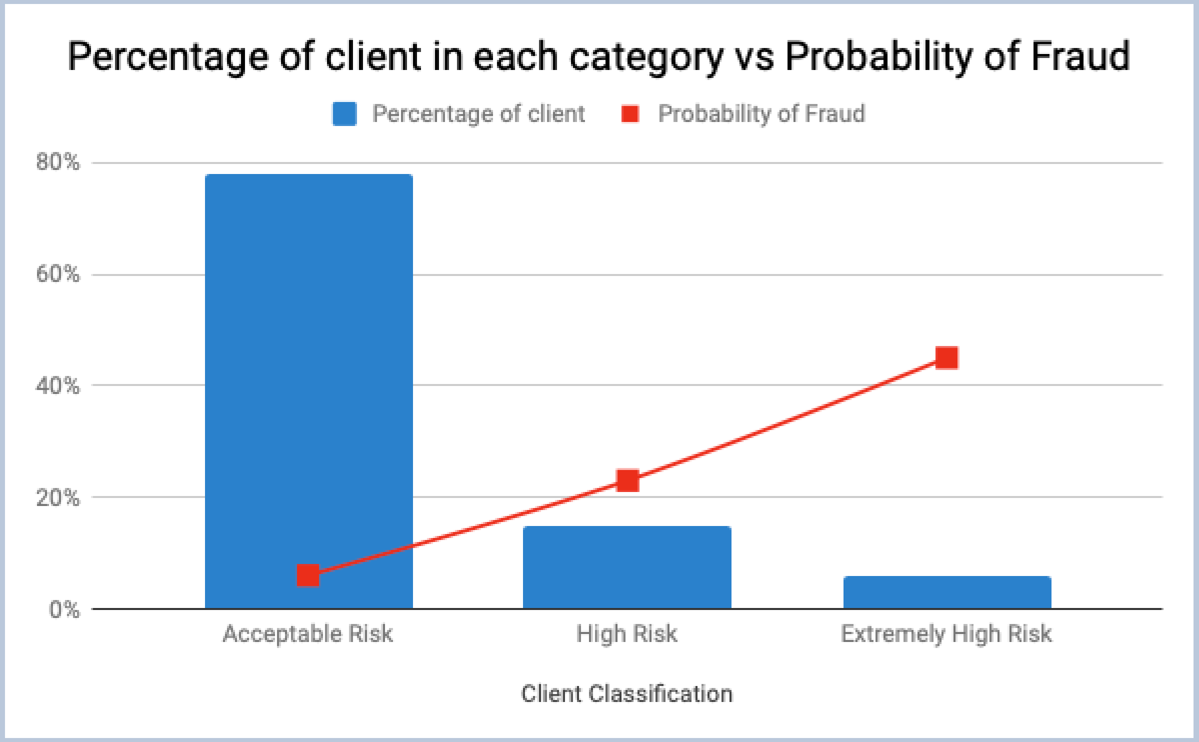

1. Client Classification
2. Risk Monitoring
3. Active Risk Management

Features of Importance & Probability Score

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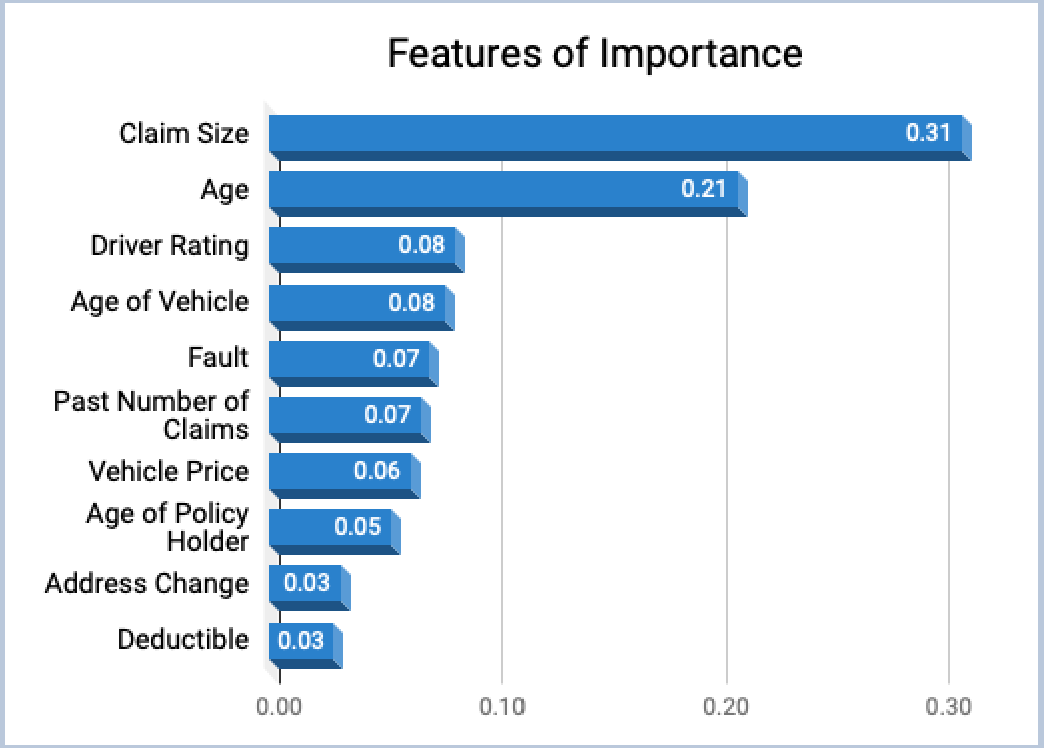

1. Another result from the balanced random forest.

2. Used for further analysis on important features.

3. Important guidance for product solution.

   a. Claim Size
   b. Age

Business Strategies

Industry standard implementation

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1. Strong anti-fraud measures, such as **enhanced data analytics** to detect fraud, and **new rules** on unfair or deceptive acts or practices

2. **Collaboration** between insurers on fraud since some frauds are elaborate and difficult to detect when an insurer only looks at their own portfolio

3. In-house dedicated **investigative services** unit

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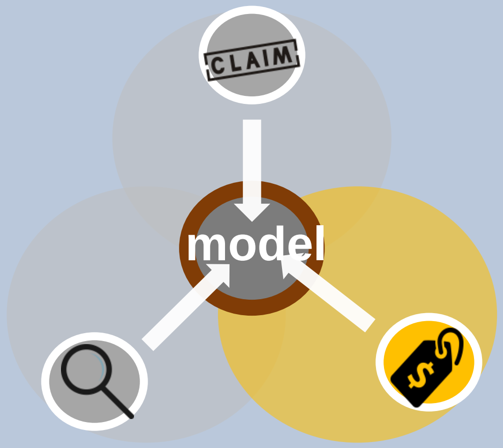
Business Strategies



01 pricing

premium = base rate
x **differentials**
x **discounts %**
+ surcharges $

Differential factor increase
– group of *high risk*

Differential factor decrease
– group of *decent risk*

Discount
– anti-fraud system installed

***New variable* of differential**
– reflecting fraud probability of the policy

Business Strategies: **examples**

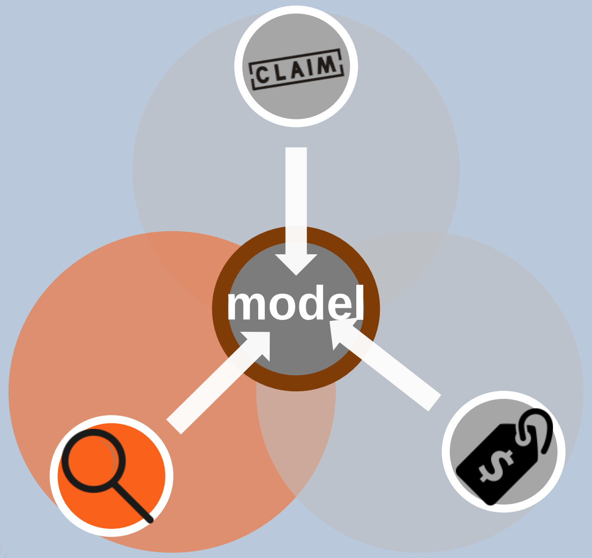
Vehicle age	Vehicle price	Past claim frequency
3 – 4 years	less than $20000 / over $69000	0.78

83% probability of committing fraud in the future claims

Vehicle age	Vehicle price	Past claim frequency
less than 2 years	$45000 - $43000	1.26

95% probability of non-fraud in the future claims

Business Strategies



02 Underwriting

- Detect the credit history of applicants, with the help of social media.
- Reduce coverage for high deductible policies.

new

+

?

Policy of high deductible amount

$50000+

80% fraud

$10000-

80% non-fraud

Business Strategies – tracking applicant credit status through social media

Why social media?

- **Over 1.7 billion** people are on social networking sites
- **35%** admit to posting something they later regretted
- **1.2 billion** users of Facebook — **23%** check their account **at least 5 times** a day
- **238+ million** users on LinkedIn

…

How?

- Seek out **inconsistent details** when investigating
- Check **secondary and friends' accounts**
- Using e-discovery in insurance fraud investigations **legally**

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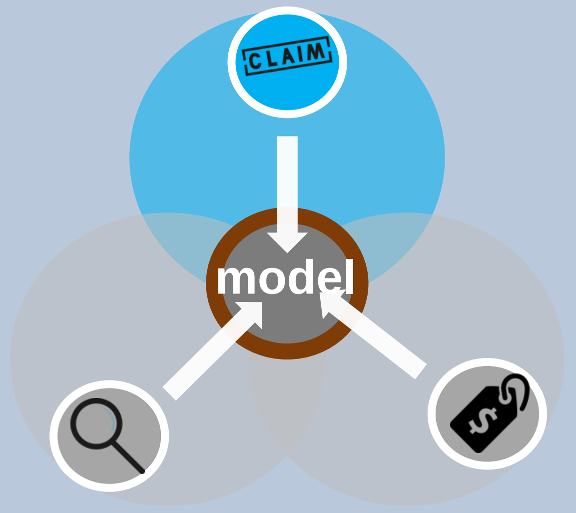
Business Strategies



03 claim

- Extra review and investigation needed for large size claims.
- Encourage claims with anti-fraud proofs.

$50000 +

78%+ fraud claim

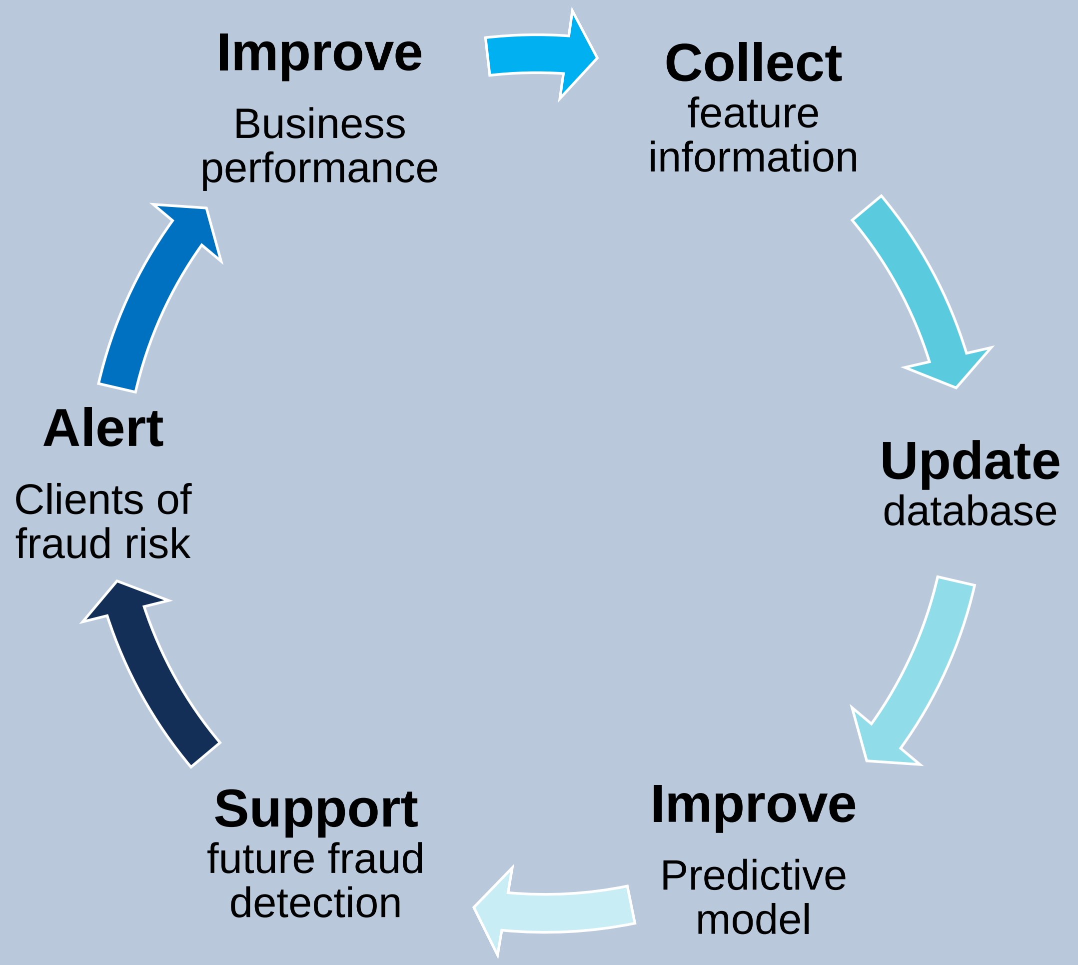
less than **8% non-fraud claim**

"24% of the surveyed believed it was acceptable to **pad an insurance claim"**

?

Claim of large size

Business Strategies: database updating after claim



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Reference

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Handling imbalanced datasets in machine learning, Baptiste Rocca, Jan 27, 2019

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Isolation-based Anomaly Detection, Fei Tony Liu, 2017

Property and Casualty Insurance Re-imagined: 2025, Deloitte Consulting

6 Steps for Preventing Insurance Fraud, DXC Technology

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Appendix: Implementation of Balanced Random Forest

Predictive Model: Balanced Random Forest

```
cleanedData=testData.copy()
cleanedData=cleanedData.drop(['RepNumber','PolicyNumber','Month','WeekOfMonth','DayOfWeek','DayOfWeekClaimed','MonthClaimed',
StrProposedList=['ClaimSize','Fault','Age','DriverRating','Deductible','VehiclePrice','PastNumberOfClaims','AgeOfVehicle','Ag
ProposedList=cleanedData[StrProposedList]
features=ProposedList.drop(['FraudFound_P'],axis=1)
target=cleanedData['FraudFound_P']
X_train, X_test, y_train, y_test =train_test_split(features, target,test_size=0.3) # 70% training and 30% test
##Balanced Random Forest
brf = BalancedRandomForestClassifier(
    n_estimators=500,
    criterion='gini',
    max_depth=None,
    min_samples_split=2,
    min_samples_leaf=1,
    min_weight_fraction_leaf=0.0,
    max_features='auto',
    max_leaf_nodes=None,
    min_impurity_decrease=0.0,
    bootstrap=True,
    oob_score=False,
    sampling_strategy=1/1.75,
    replacement=True,
    n_jobs=1,
    random_state=None,
    verbose=0,
    warm_start=False,
    class_weight={1:1.5,-1:1}
)
brf.fit(X_train, y_train)
y_pred = brf.predict(X_test)
y_score=brf.predict_proba(X_test)
```

Data Processing

```
##VehicleCategory
testData=OHRearrange(testData,'VehicleCategory')
testData=OHRearrange(testData,'MaritalStatus')
testData=OHRearrange(testData,'PolicyType')
testData=OHRearrange(testData,'BasePolicy')
testData=OHRearrange(testData,'Make')
##Sex: F-1, M-0
testData['Sex']=testData['Sex'].map({'Female':1,'Male':0})
##AgentType: Internal-1, External-0
testData['AgentType']=testData['AgentType'].map({'Internal':1,'External':0})
##PoliceReportFiled,WitnessPresent
testData['PoliceReportFiled']=testData['PoliceReportFiled'].map({'Yes':1,'No':0})
testData['WitnessPresent']=testData['WitnessPresent'].map({'Yes':1,'No':0})
##Fault: Policyholder-1, Third Party-0
testData['Fault']=testData['Fault'].map({'Policy Holder':1,'Third Party':0})
##DriverRating: we use average rating for the "NA" values in the dataset
testData['DriverRating']=testData['DriverRating'].fillna(averageNA(testData['DriverRating']))
##AccidentArea: Urban-1, Rural-0
testData['AccidentArea']=testData['AccidentArea'].map({'Urban':1,'Rural':0})
##Age
testData['Age']=testData['Age'].fillna(averageZERO(testData['Age']))
##VehiclePrice
VPdict={
    'less than 20000':10000,
    '20000 to 29000':25000,
    '30000 to 39000':35000,
    '40000 to 59000':50000,
    '60000 to 69000':65000,
    'more than 69000': 80000
}
```

Data Processing

```
testData['PastNumberOfClaims']=testData['PastNumberOfClaims'].map(PNCdict)
##AgeOfVehicle
AOVdict={
    'new':0,
    '2 years':2,
    '3 years':3,
    '4 years':4,
    '5 years':5,
    '6 years':6,
    '7 years':7,
    'more than 7':9
}
testData['AgeOfVehicle']=testData['AgeOfVehicle'].map(AOVdict)
##AgeOfPolicyHolder
def AOPHmap(x):
    if x=='over 65':
        return 70
    else:
        return (int(x[:2])+int(x[6:8]))/2
testData['AgeOfPolicyHolder']=testData['AgeOfPolicyHolder'].map(AOPHmap)
##Days_Policy_Claim
testData['Days_Policy_Claim']=testData['Days_Policy_Claim'].map({'more than 30':35,'15 to 30':22.5,'8 to 15':11.5,'none':35})
##AddressChange_Claim
ACCdict={
    'no change':0,
    'under 6 months':0.5,
    '1 year':1,
    '2 to 3 years':2.5,
    '4 to 8 years':6
}
```

Data Processing

```
testData['AddressChange_Claim']=testData['AddressChange_Claim'].map(ACCdict)
##NumberOfCars
NOCdict={
    '1 vehicle':1,
    '2 vehicles':2,
    '3 to 4':3.5,
    '5 to 8':6.5,
    'more than 8':9
}
testData['NumberOfCars']=testData['NumberOfCars'].map(NOCdict)
##FraudFound_P
testData['FraudFound_P']=testData['FraudFound_P'].map({0:1,1:-1})
cleanedData=testData.copy()
cleanedData=cleanedData.drop(['RepNumber','PolicyNumber','Month','WeekOfMonth','DayOfWeek','DayOfWeekClaimed','MonthClaimed',
correlation_matrix = cleanedData.corr()

fig = plt.figure(figsize=(12,9))

sns.heatmap(correlation_matrix,square = True)

plt.show()
```

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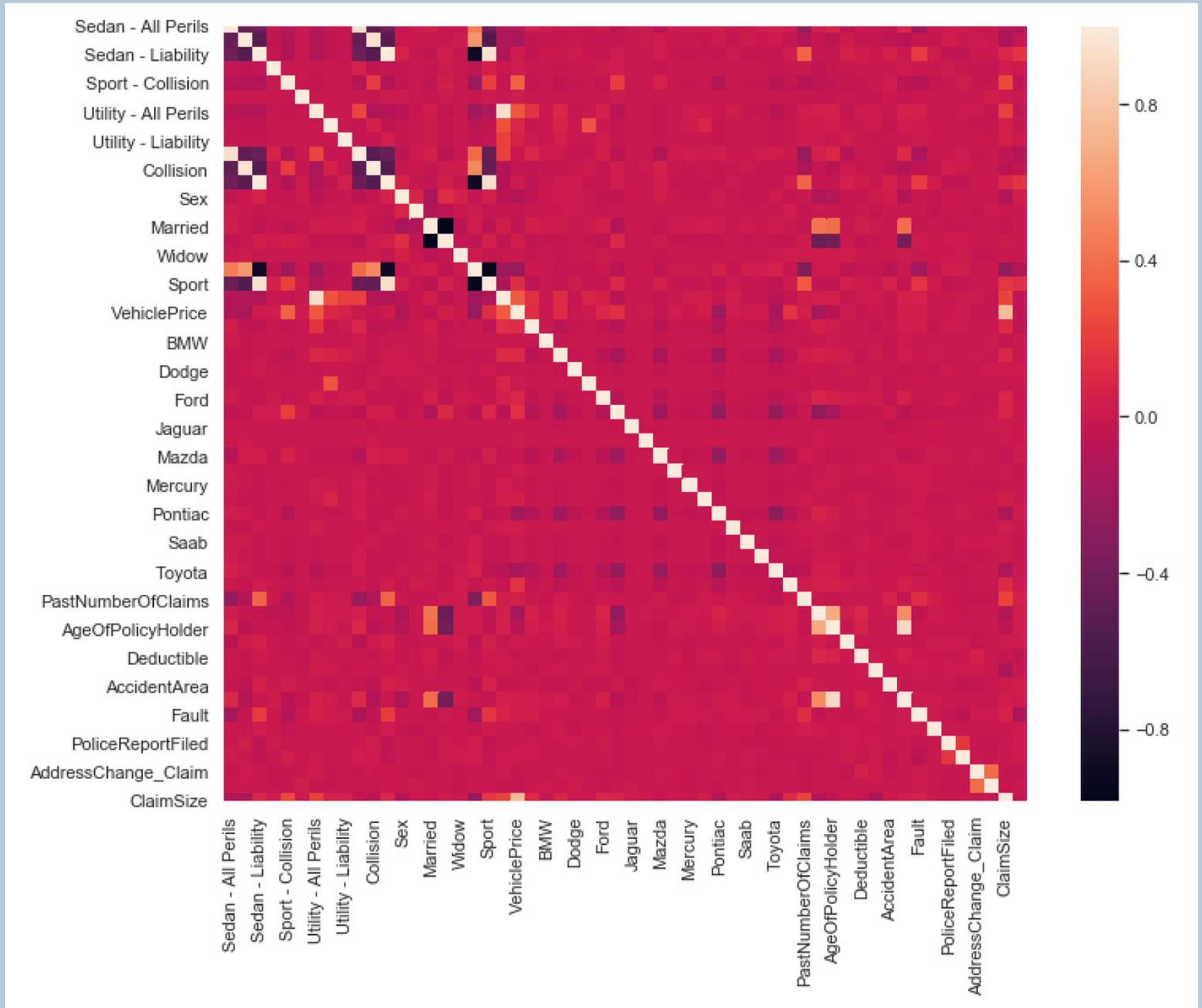
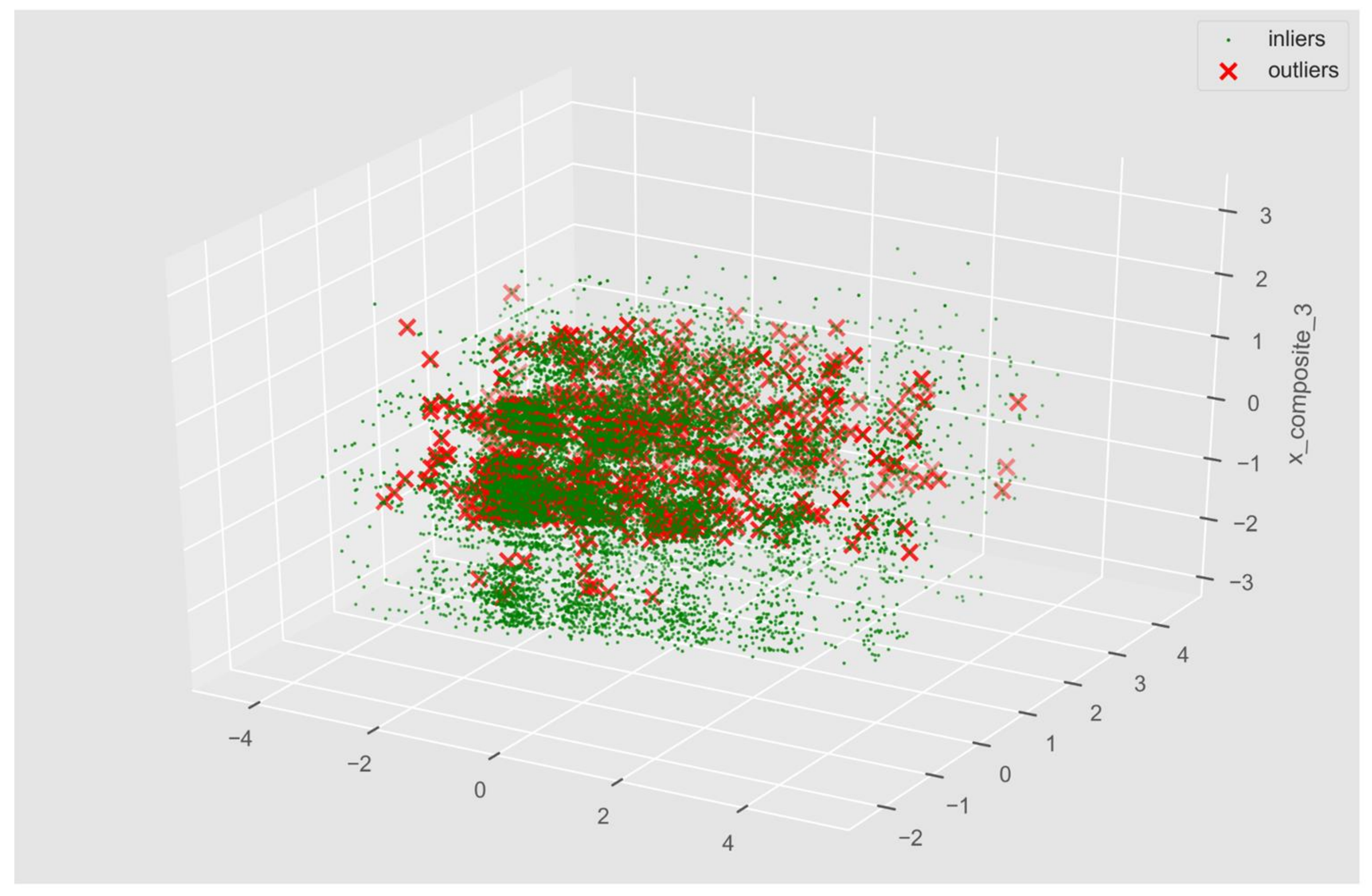
Correlation Heat Map



Initial Cluster Observation



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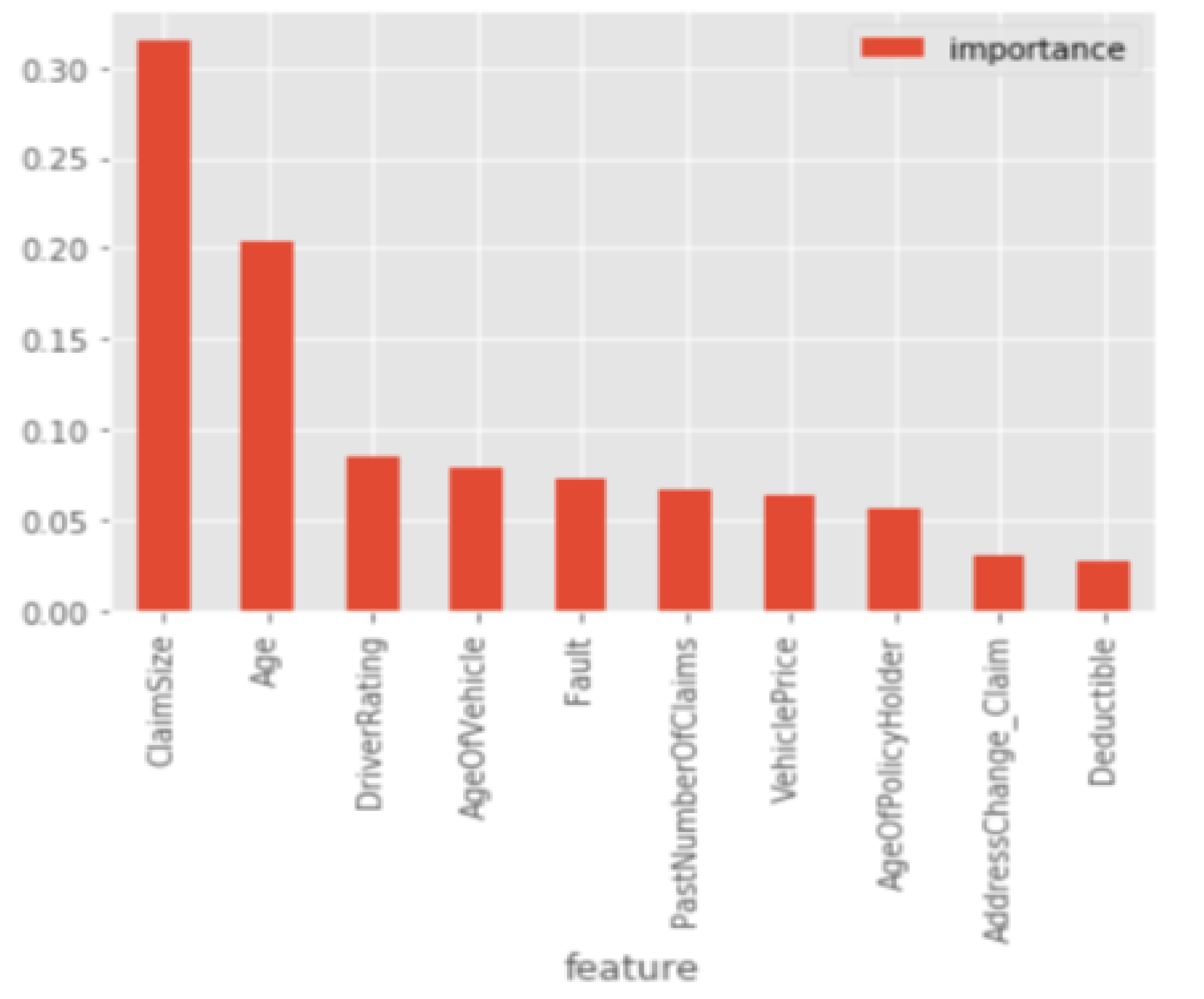
Features of Importance

	feature	importance
0	ClaimSize	0.310363
2	Age	0.209719
3	DriverRating	0.083327
7	AgeOfVehicle	0.078674
1	Fault	0.071845
6	PastNumberOfClaims	0.067893
5	VehiclePrice	0.063279
8	AgeOfPolicyHolder	0.054409
9	AddressChange_Claim	0.031732
4	Deductible	0.028760



Important Features Correlation

	VehiclePrice	PastNumberl	AgeOfVehicl	AgeOfPolicyl	AgentType	Deductible	DriverRating	AccidentAre	Age	Fault	PoliceReporl	WitnessPres	AddressChar	NumberOfCa	ClaimSize	FraudFound_	Days_Policy_Claim
VehiclePrice	100%	5%	-17%	-8%	1%	-1%	1%	-1%	-10%	4%	0%	2%	-1%	-2%	75%	-4%	0%
PastNumberOfClaims	5%	100%	0%	-2%	0%	0%	-1%	7%	-2%	12%	0%	-2%	-2%	-1%	23%	6%	4%
AgeOfVehicle	-17%	0%	100%	67%	3%	9%	0%	1%	72%	-3%	1%	-1%	0%	1%	-10%	3%	1%
AgeOfPolicyHolder	-8%	-2%	67%	100%	0%	6%	0%	0%	95%	-1%	0%	0%	0%	0%	-5%	3%	1%
AgentType	1%	0%	3%	0%	100%	0%	0%	0%	0%	-1%	1%	2%	-3%	0%	2%	2%	1%
Deductible	-1%	0%	9%	6%	0%	100%	2%	0%	6%	1%	1%	0%	6%	-1%	-1%	-3%	0%
DriverRating	1%	-1%	0%	0%	0%	2%	100%	0%	0%	1%	1%	2%	1%	1%	-14%	-1%	0%
AccidentArea	-1%	7%	1%	0%	0%	0%	0%	100%	0%	-1%	0%	-3%	-2%	0%	1%	3%	0%
Age	-10%	-2%	72%	95%	0%	6%	0%	0%	100%	-1%	0%	-1%	0%	0%	-7%	3%	0%
Fault	4%	12%	-3%	-1%	-1%	1%	1%	-1%	-1%	100%	-3%	-6%	1%	1%	7%	-13%	2%
PoliceReportFiled	0%	0%	1%	0%	1%	1%	1%	0%	0%	-3%	100%	16%	-1%	-3%	0%	1%	0%
WitnessPresent	2%	-2%	-1%	0%	2%	0%	2%	-3%	-1%	-6%	16%	100%	0%	-1%	1%	1%	1%
AddressChange_Claim	-1%	-2%	0%	0%	-3%	6%	1%	-2%	0%	1%	-1%	0%	100%	39%	-1%	-2%	-1%
NumberOfCars	-2%	-1%	1%	0%	0%	-1%	1%	0%	0%	1%	-3%	-1%	39%	100%	-1%	-1%	0%
ClaimSize	75%	23%	-10%	-5%	2%	-1%	-14%	1%	-7%	7%	0%	1%	-1%	-1%	100%	-2%	1%
FraudFound_P	-4%	6%	3%	3%	2%	-3%	-1%	3%	3%	-13%	1%	1%	-2%	-1%	-2%	100%	1%
Days_Policy_Claim	0%	4%	1%	1%	1%	0%	0%	0%	0%	2%	0%	1%	-1%	0%	1%	1%	100%

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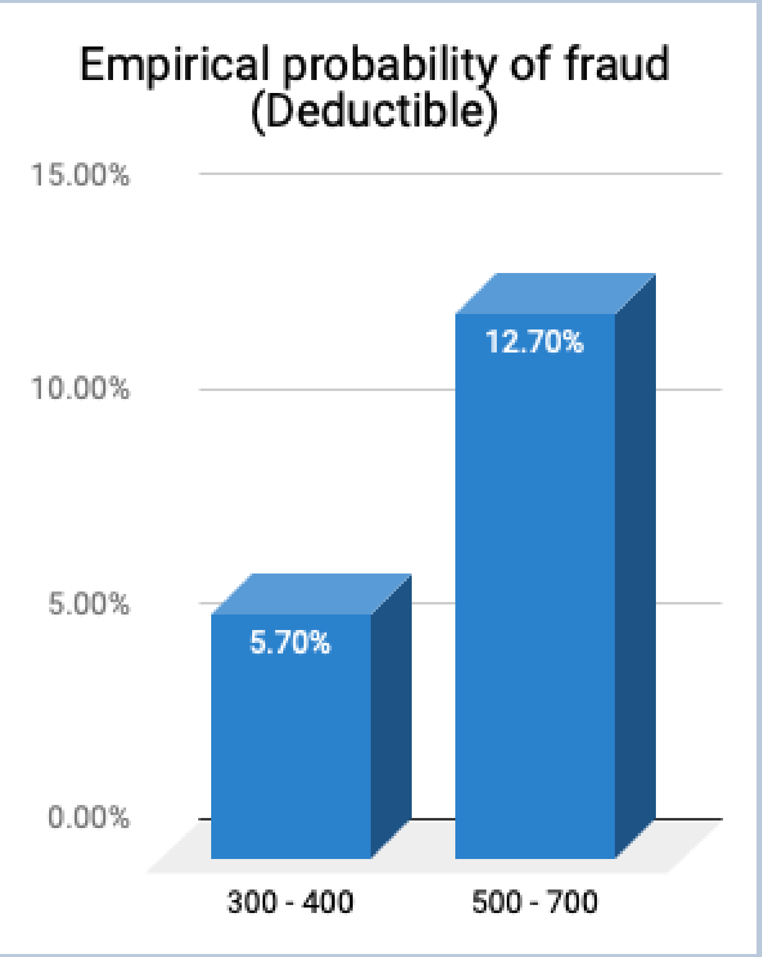
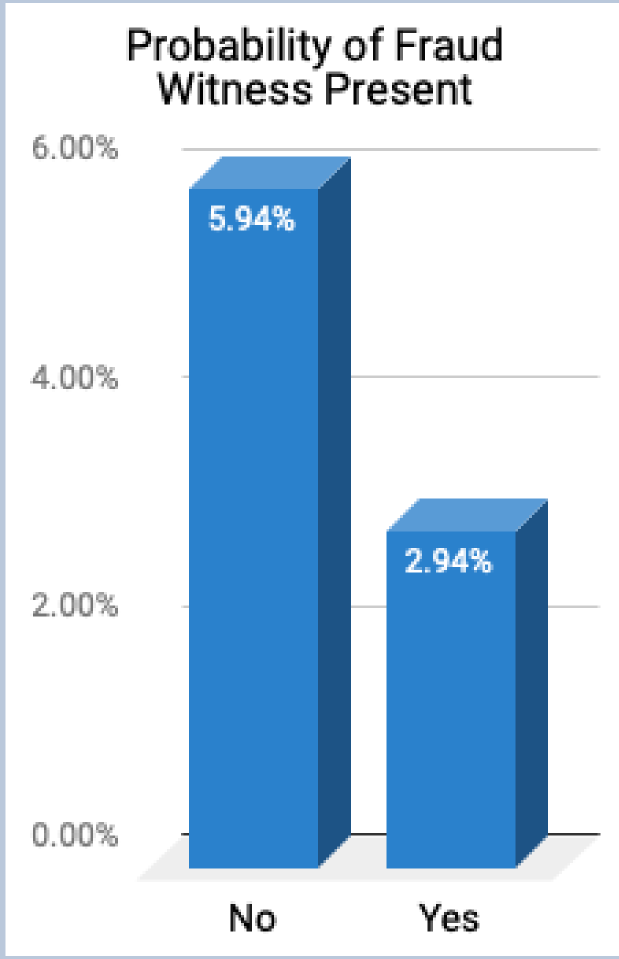
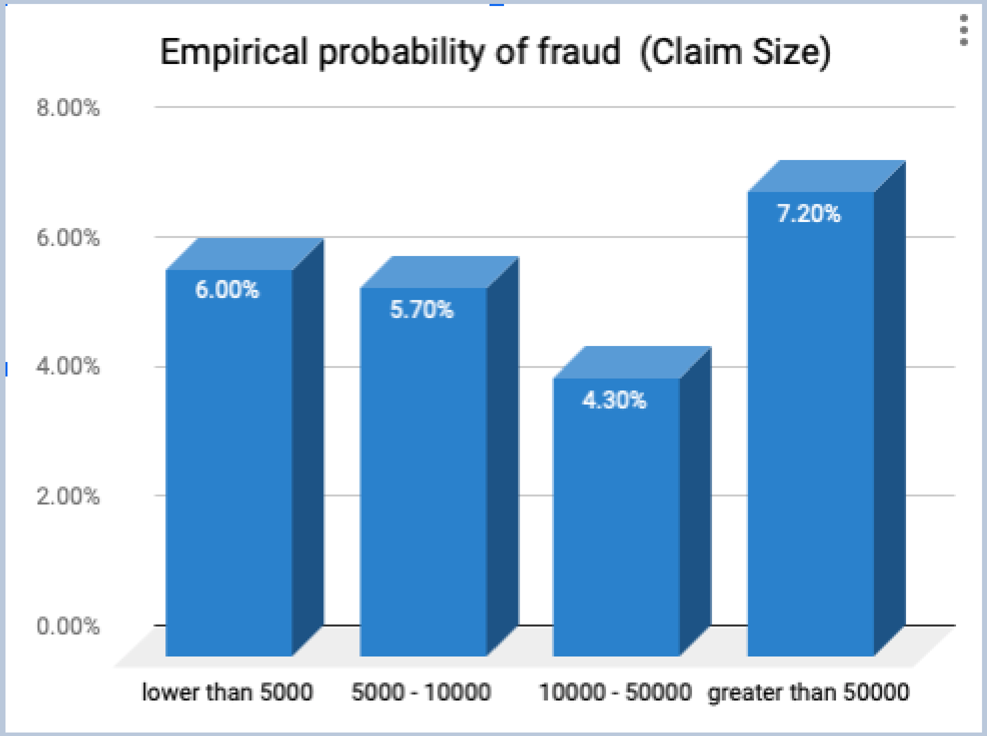
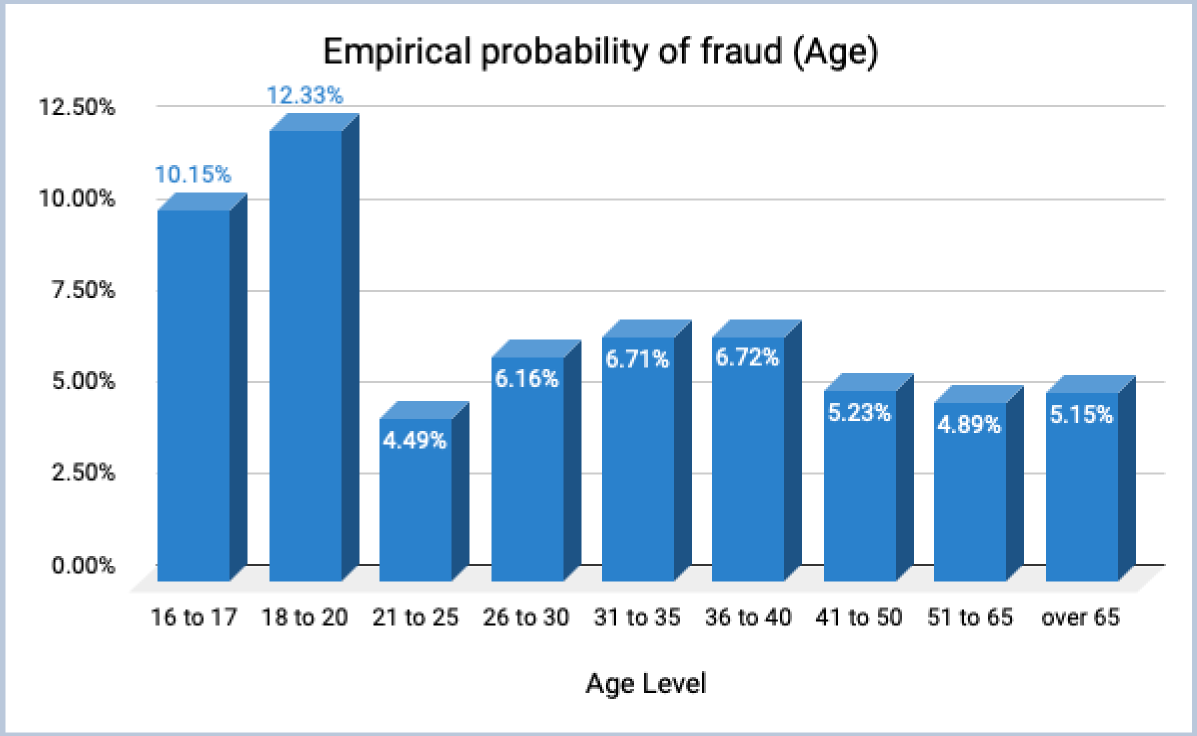
Low Correlation Features



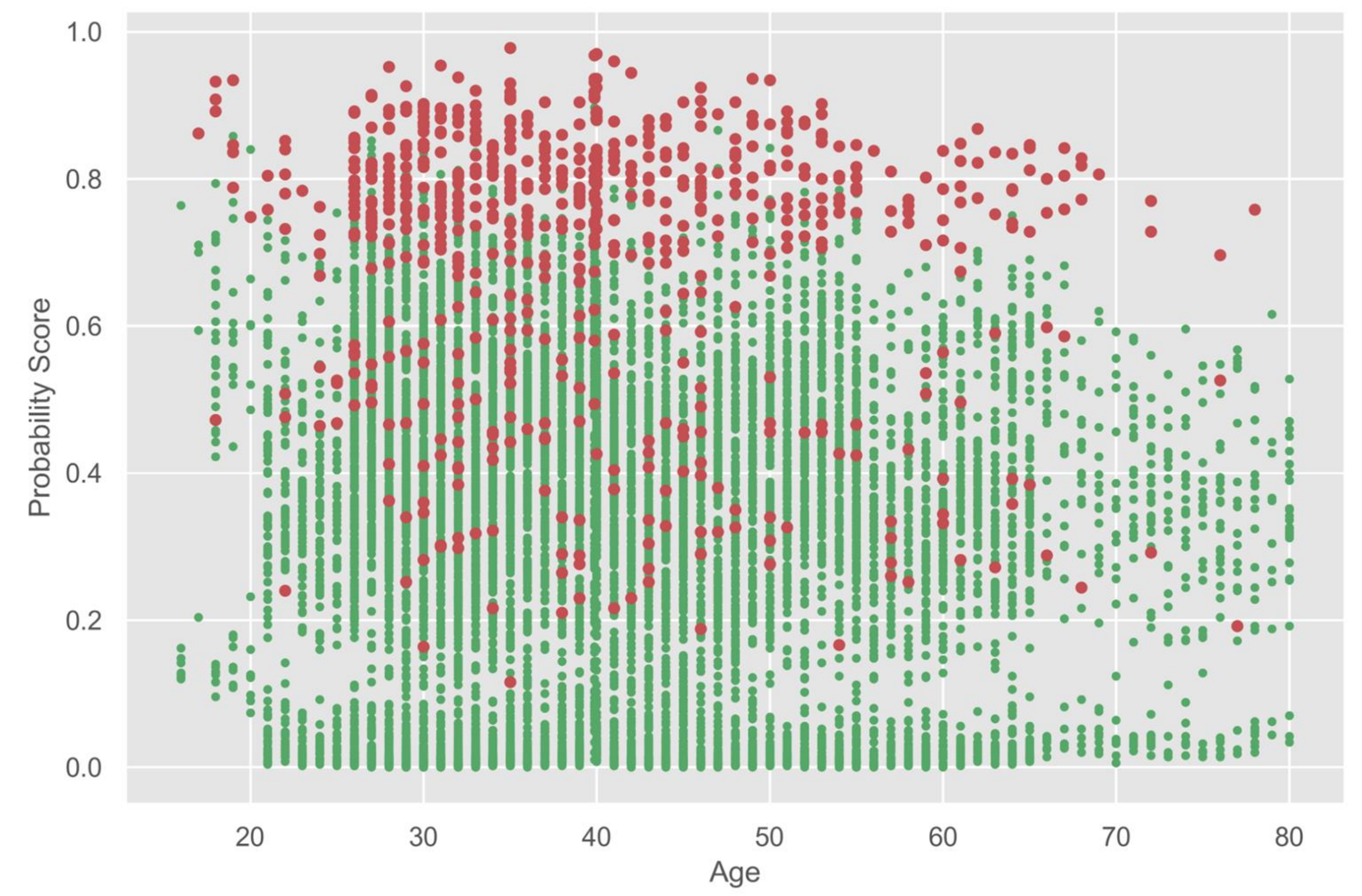


High Correlation Features





Probability Score vs Age



Red: Fraud

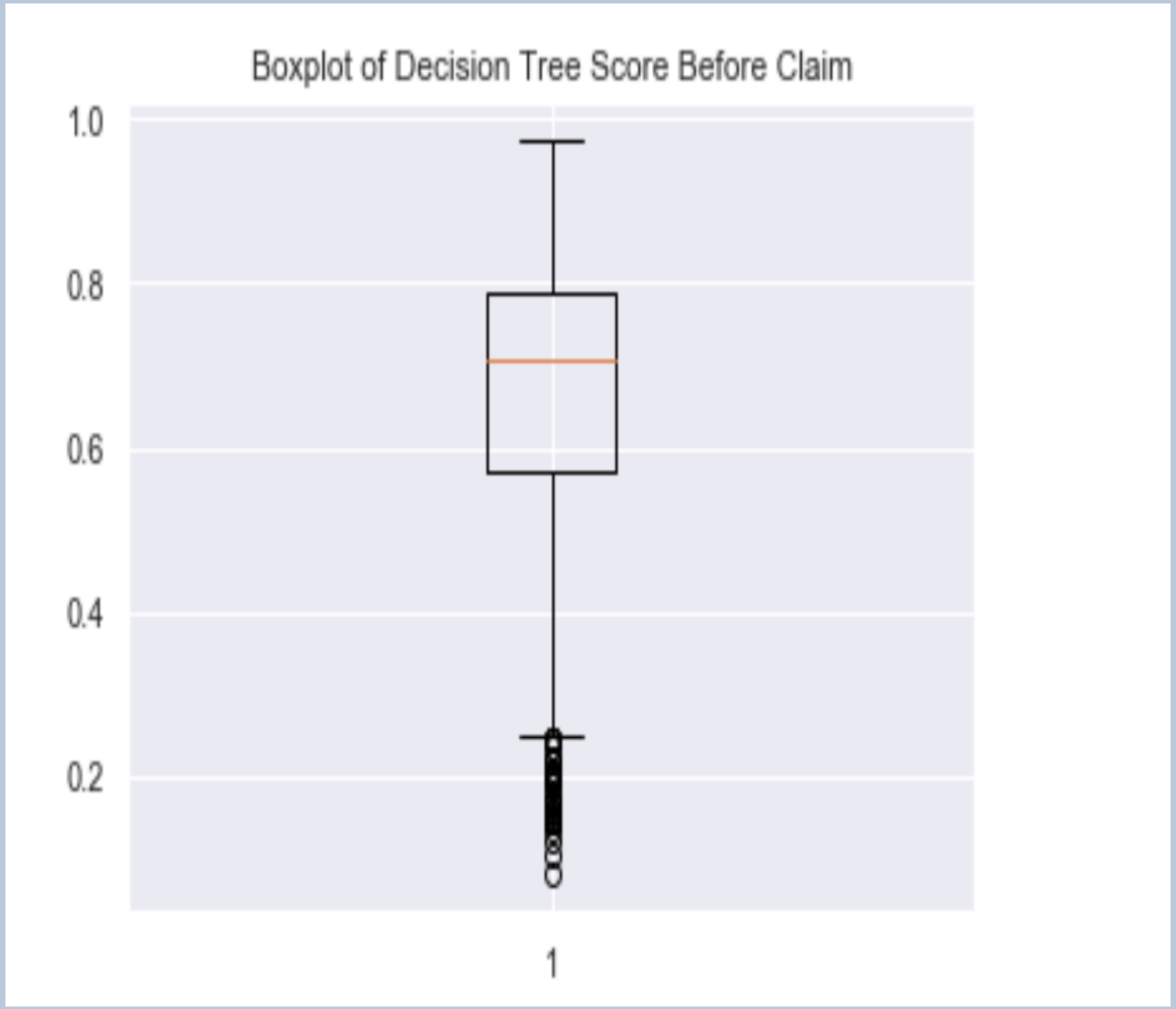
Green: Normal

Probability Score vs Claim Size

Red: Fraud

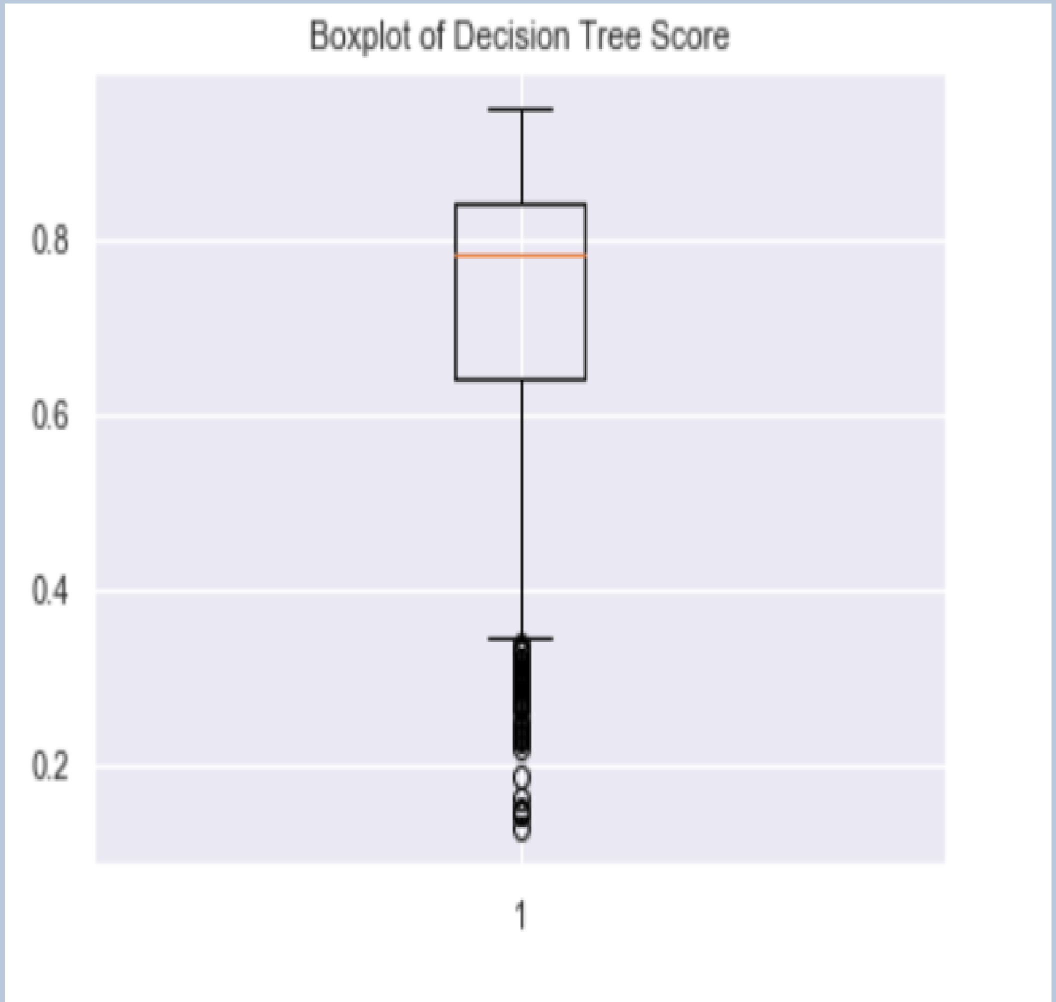
Green: Normal

Pre - Claim Probability Score



Minimum	0.079
Q1	0.572
Median	0.709
Q3	0.788
Maximum	0.976

Post - Claim Probability Score



Minimum	0.100
Q1	0.678
Median	0.744
Q3	0.834
Maximum	0.976

Generated Report On Features

```
(Fraud) ClaimSize Probability Score Between [0.068,0.66): 23713.404474548537
(Fraud) ClaimSize Probability Score Between [0.66,0.77): 23664.10850995O587
(Fraud) ClaimSize Probability Score Between [0.77,0.836): 24376.14526478382
(Fraud) ClaimSize Probability Score Between [0.836,0.976): 28637.8888620115
(Overall) ClaimSize with Probability Score Between [0.068,0.66): 24069.153214415423
(Overall) ClaimSize with Probability Score Between [0.66,0.77): 31079.52269031254
(Overall) ClaimSize with Probability Score Between [0.77,0.836): 27833.71330780301
(Overall) ClaimSize with Probability Score Between [0.836,0.976): 30772.951054406352
(Fraud) Fault Probability Score Between [0.068,0.66): 0.9883040935672515
(Fraud) Fault Probability Score Between [0.66,0.77): 0.9939759036144579
(Fraud) Fault Probability Score Between [0.77,0.836): 0.9884393063583815
(Fraud) Fault Probability Score Between [0.836,0.976): 0.867816091954023
(Overall) Fault with Probability Score Between [0.068,0.66): 0.9521494370522006
(Overall) Fault with Probability Score Between [0.66,0.77): 0.9907235621521335
(Overall) Fault with Probability Score Between [0.77,0.836): 0.9819819819819819
(Overall) Fault with Probability Score Between [0.836,0.976): 0.8697916666666666
```

Generated Report On Features

```
(Fraud) Age Probability Score Between [0.068,0.66): 38.8517365614642
(Fraud) Age Probability Score Between [0.66,0.77): 41.4489715020914
(Fraud) Age Probability Score Between [0.77,0.836): 40.4488263121987
(Fraud) Age Probability Score Between [0.836,0.976): 38.0013491957004
(Overall) Age with Probability Score Between [0.068,0.66): 40.966704015088
(Overall) Age with Probability Score Between [0.66,0.77): 39.303828245129
(Overall) Age with Probability Score Between [0.77,0.836): 39.866452444662
(Overall) Age with Probability Score Between [0.836,0.976): 38.097421278282
(Fraud) DriverRating Probability Score Between [0.068,0.66): 2.5555555555555
(Fraud) DriverRating Probability Score Between [0.66,0.77): 2.397590361445783
(Fraud) DriverRating Probability Score Between [0.77,0.836): 2.46820809248554
(Fraud) DriverRating Probability Score Between [0.836,0.976): 2.712643678160919
(Overall) DriverRating with Probability Score Between [0.068,0.66): 2.50767255612330
(Overall) DriverRating with Probability Score Between [0.66,0.77): 2.4860853432282
(Overall) DriverRating with Probability Score Between [0.77,0.836): 2.46846846846846
(Overall) DriverRating with Probability Score Between [0.836,0.976): 2.671875
```

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Generated Report On Features

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(Fraud) Deductible Probability Score Between [0.068,0.66): 410.5263157894737
(Fraud) Deductible Probability Score Between [0.66,0.77): 412.0481927710843б
(Fraud) Deductible Probability Score Between [0.77,0.836): 411.560693641б185
(Fraud) Deductible Probability Score Between [0.836,0.976): 418.39080459770116
(Overall) Deductible with Probability Score Between [0.068,0.66): 409.85158648925284
(Overall) Deductible with Probability Score Between [0.66,0.77): 409.4619666048238
(Overall) Deductible with Probability Score Between [0.77,0.836): 411.7117117117117
(Overall) Deductible with Probability Score Between [0.836,0.976): 417.7083333333333
(Fraud) VehiclePrice Probability Score Between [0.068,0.66): 36081.87134502924
(Fraud) VehiclePrice Probability Score Between [0.66,0.77): 34006.02409638554
(Fraud) VehiclePrice Probability Score Between [0.77,0.836): 37052.02312138728
(Fraud) VehiclePrice Probability Score Between [0.836,0.976): 43189.65517241379
(Overall) VehiclePrice with Probability Score Between [0.068,0.66): 35177.20061412487
(Overall) VehiclePrice with Probability Score Between [0.66,0.77): 43061.22448979592
(Overall) VehiclePrice with Probability Score Between [0.77,0.836): 41238.738738738735
(Overall) VehiclePrice with Probability Score Between [0.836,0.976): 45468.75
```

Generated Report On Features

```
(Fraud) PastNumberOfClaims Probability Score Between [0.068,0.66): 1.7719298245614035
(Fraud) PastNumberOfClaims Probability Score Between [0.66,0.77): 2.2048192771084336
(Fraud) PastNumberOfClaims Probability Score Between [0.77,0.836): 1.4277456647398843
(Fraud) PastNumberOfClaims Probability Score Between [0.836,0.976): 0.7816091954022989
(Overall) PastNumberOfClaims with Probability Score Between [0.068,0.66): 2.1361310133060387
(Overall) PastNumberOfClaims with Probability Score Between [0.66,0.77): 1.163265306122449
(Overall) PastNumberOfClaims with Probability Score Between [0.77,0.836): 1.2657657657657657
(Overall) PastNumberOfClaims with Probability Score Between [0.836,0.976): 0.7395833333333334
(Fraud) AgeOfVehicle Probability Score Between [0.068,0.66): 6.847953216374269
(Fraud) AgeOfVehicle Probability Score Between [0.66,0.77): 6.945783132530121
(Fraud) AgeOfVehicle Probability Score Between [0.77,0.836): 6.664739884393064
(Fraud) AgeOfVehicle Probability Score Between [0.836,0.976): 6.068965517241379
(Overall) AgeOfVehicle with Probability Score Between [0.068,0.66): 6.86399692937564
(Overall) AgeOfVehicle with Probability Score Between [0.66,0.77): 6.296846011131725
(Overall) AgeOfVehicle with Probability Score Between [0.77,0.836): 6.288288288288288
(Overall) AgeOfVehicle with Probability Score Between [0.836,0.976): 5.666666666666667
```

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Generated Report On Features

```
(Fraud) AgeOfPolicyHolder Probability Score Between [0.068,0.66): 38.27485380116959
(Fraud) AgeOfPolicyHolder Probability Score Between [0.66,0.77): 40.174698795180724
(Fraud) AgeOfPolicyHolder Probability Score Between [0.77,0.836): 39.55780346820809
(Fraud) AgeOfPolicyHolder Probability Score Between [0.836,0.976): 35.82183908045977
(Overall) AgeOfPolicyHolder with Probability Score Between [0.068,0.66): 39.689163254861825
(Overall) AgeOfPolicyHolder with Probability Score Between [0.66,0.77): 37.601113172541744
(Overall) AgeOfPolicyHolder with Probability Score Between [0.77,0.836): 37.945945945945944
(Overall) AgeOfPolicyHolder with Probability Score Between [0.836,0.976): 34.53125
(Fraud) AddressChange_Claim Probability Score Between [0.068,0.66): 0.42105263157894735
(Fraud) AddressChange_Claim Probability Score Between [0.66,0.77): 0.4006024096385542
(Fraud) AddressChange_Claim Probability Score Between [0.77,0.836): 0.2658959537572254
(Fraud) AddressChange_Claim Probability Score Between [0.836,0.976): 0.5
(Overall) AddressChange_Claim with Probability Score Between [0.068,0.66): 0.4176688433981575
(Overall) AddressChange_Claim with Probability Score Between [0.66,0.77): 0.29035250463821893
(Overall) AddressChange_Claim with Probability Score Between [0.77,0.836): 0.240990990990991
(Overall) AddressChange_Claim with Probability Score Between [0.836,0.976): 0.5234375
```

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Generated Report On Features

```
(Fraud) FraudFound_P Probability Score Between [0.068,0.66): -1.0
(Fraud) FraudFound_P Probability Score Between [0.66,0.77): -1.0
(Fraud) FraudFound_P Probability Score Between [0.77,0.836): -1.0
(Fraud) FraudFound_P Probability Score Between [0.836,0.976): -1.0
(Overall) FraudFound_P with Probability Score Between [0.068,0.66): 0.956243602865916
(Overall) FraudFound_P with Probability Score Between [0.66,0.77): 0.3840445269016697 4
(Overall) FraudFound_P with Probability Score Between [0.77,0.836): -0.5585585585585585
(Overall) FraudFound_P with Probability Score Between [0.836,0.976): -0.8125
```