SMOKER PROPENSITY AND SMOKER LIAR MODEL

Introduction

Smoker Propensity Model: Predicts which applicant is a smoker

Smoker Liar Model: Predicts which applicant is a smoker liar

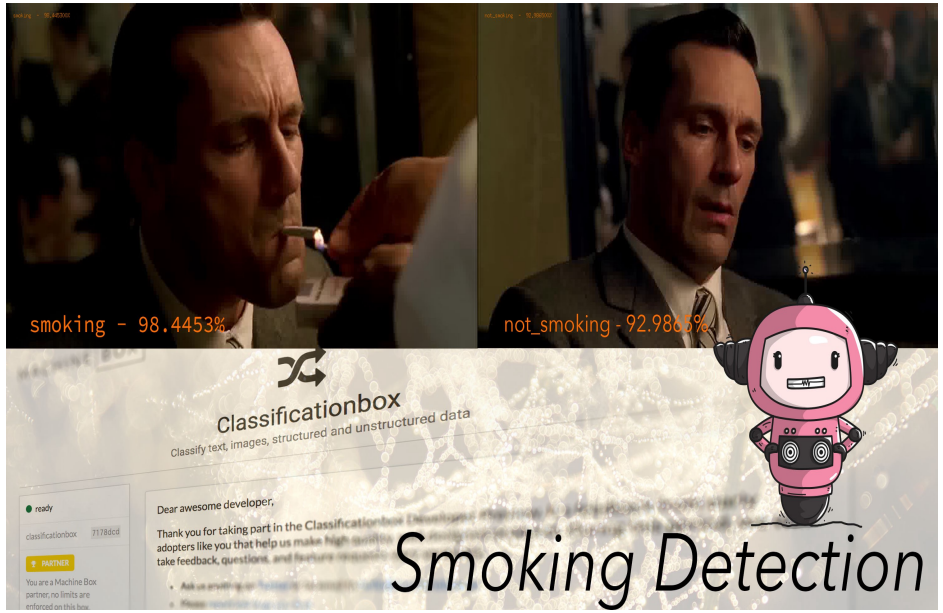
Model characteristics:

- Same performance metrics but different distribution and results

- Follow same procedure:
  - Problem definition
  - Data acquisition
  - Modeling
  - Evaluation
  - Features
  - Experimentation

PROBLEM DEFINITION

- An insurance fraud: Applicants giving false information about their tobacco use.
- Build two models to support the accelerated underwriting process in flagging applicants who are likely to be smokers and smoker liars.
- Supervised Machine Learning: figuring out the patterns based on input-output pairs and then apply the pattern to other inputs to find outputs.



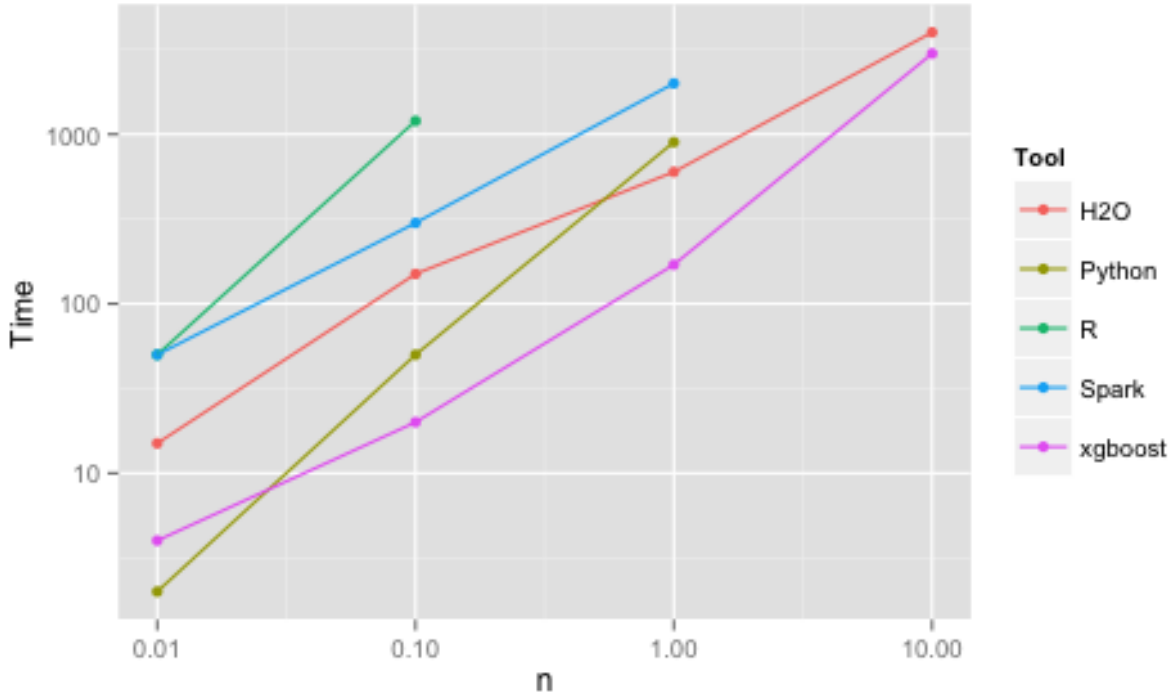
DATA ACQUISITION

- Data collected from: Application part A, application part B, lab results, therapeutics, and prescriptions

  - Gender
  - Height
  - Weight
  - Marital status
  - Age
  - Product name
  - Birth country
  - Income
  - Occupation
  - Range values & Range texts
  - Therapeutics
  - Part B application questions

- The final model has ~72000 rows and 17 columns, 7 of which contain categorical (non-numerical) values.

MODELING



Extreme Gradient Boosting (XGBoost)

- **Fast**:

"I also tried xgboost, a popular library for boosting which is capable to build random forests as well. It is fast, memory efficient and of high accuracy"– Szilard Pafka

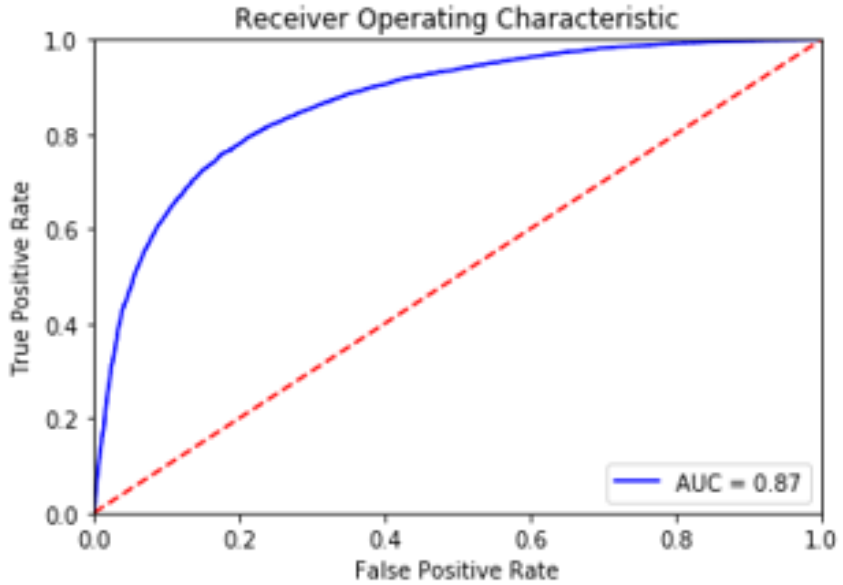
- **Popular**: go-to algorithm used for data science competition

"When in doubt, use xgboost." – Owen Zhang

EVALUATION

AUC Score: Area Under the Curve

- Measures how well the model distinguishes between two target variables
- Should be 0.5 < AUC < 1, 1 is for 100% accurate prediction while 0 is 100% wrong prediction.



Example of a AUC curve

Accuracy score:

$$\text{Accuracy} = \frac{\text{Number of accurate predictions}}{\text{Total number of predictions}}$$

- Doesn't work for imbalanced datasets

	Predicted True	Predicted False
Real True	850	35
Real False	45	70

$$\frac{70 + 850}{1000} = 92\%$$

Example of accuracy score with imbalanced dataset

EVALUATION

Precision score:

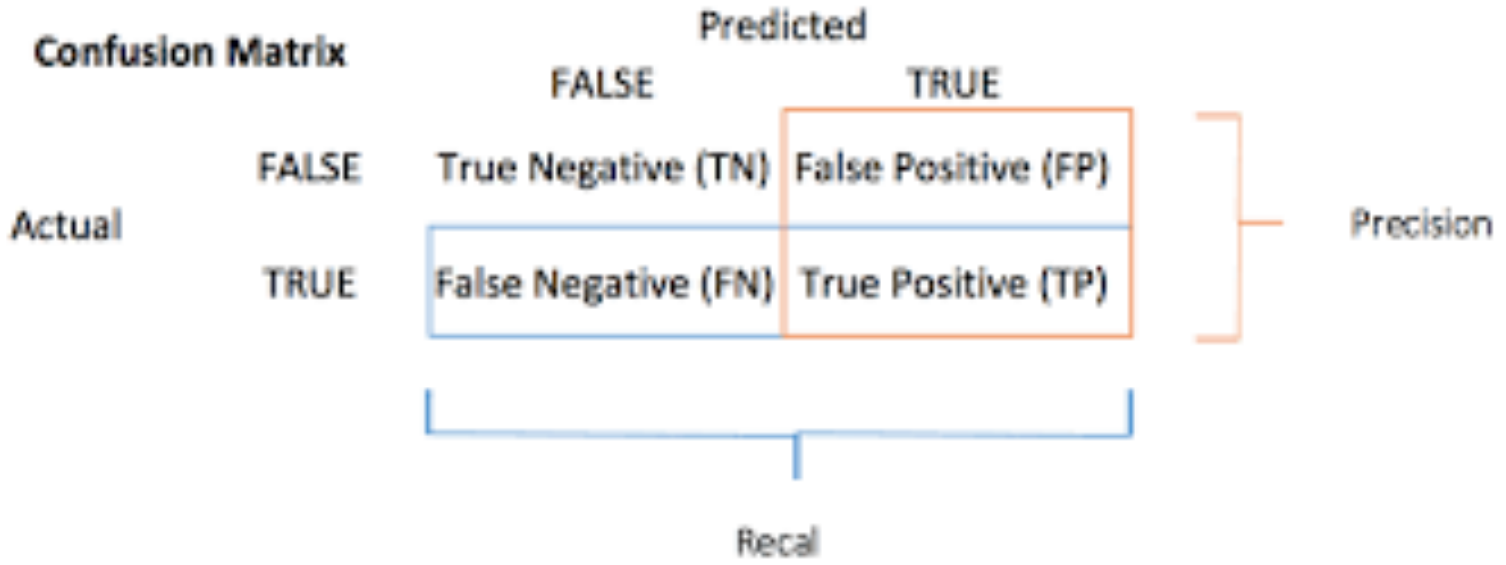
$$\text{Precision} = \frac{\text{True Positive}}{\text{Total Predicted Positive}}$$

What proportion of positive identifications was correct?

Recall score:

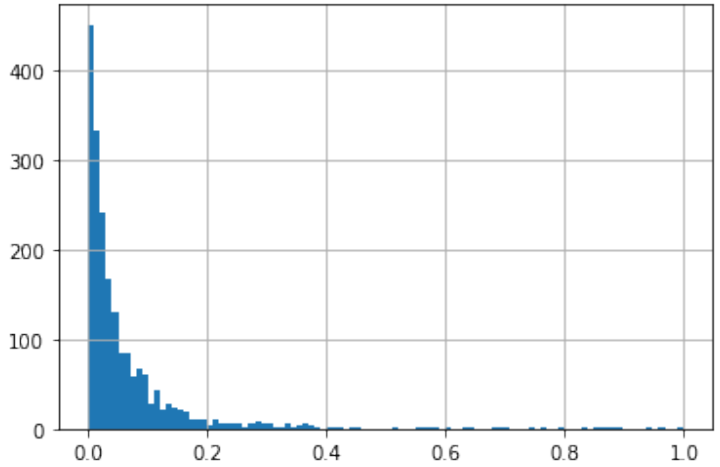
$$\text{Recall} = \frac{\text{True Positive}}{\text{Total Actual Positive}}$$

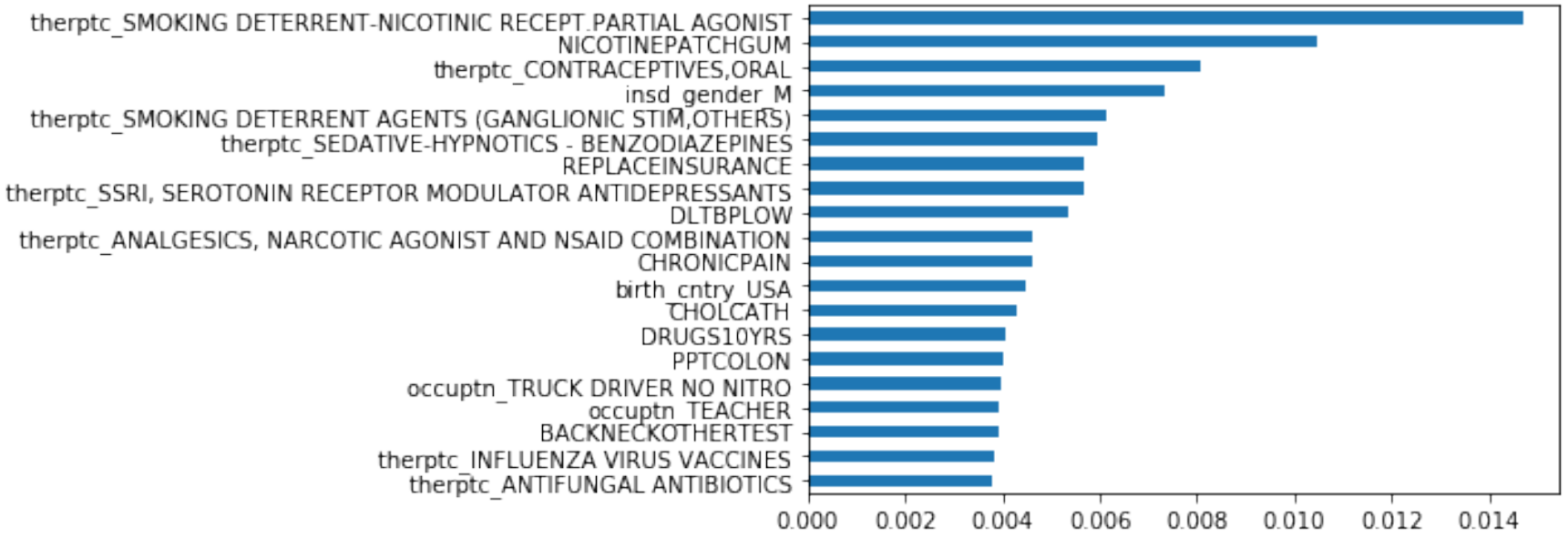
What proportion of actual positives was identified correctly?



SMOKER PROPENSITY MODEL

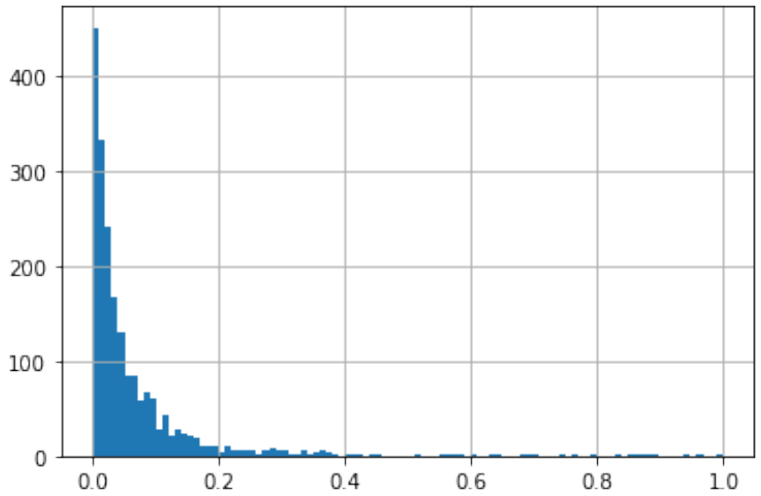
AUC score: 0.74





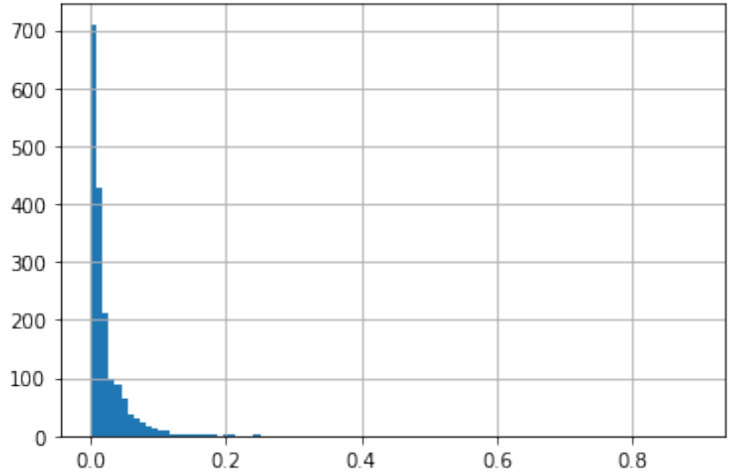
SMOKER PROPENSITY MODEL

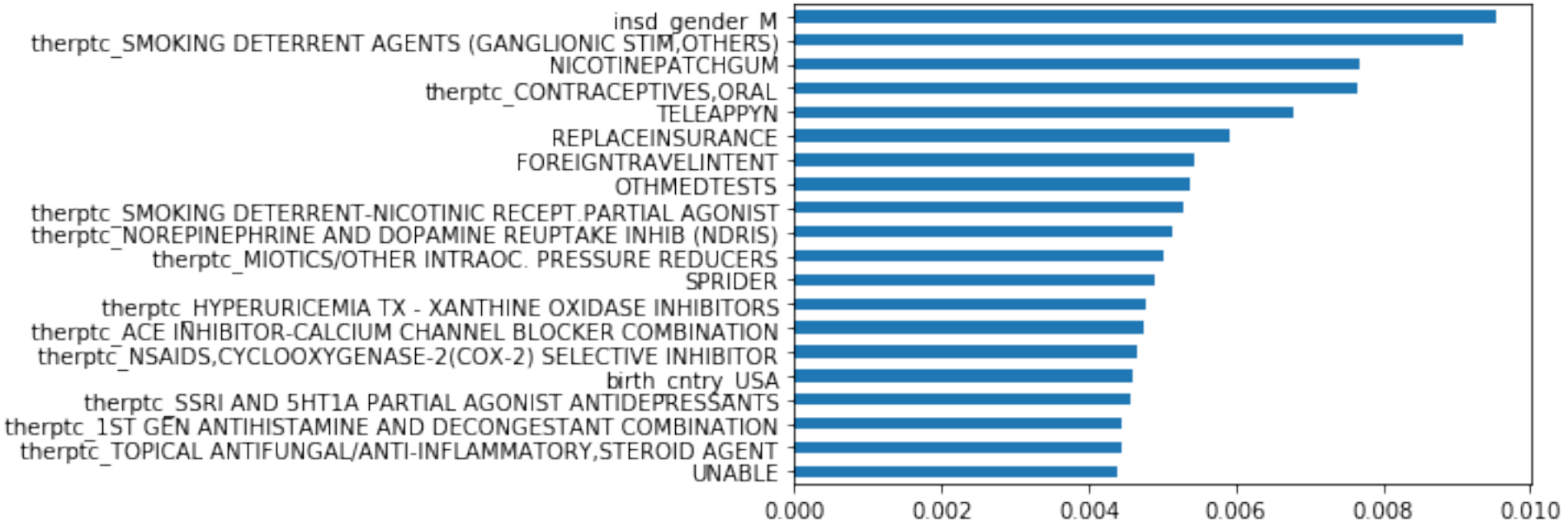
Threshold	Precision	Recall	Accuracy
0.1	0.21	0.44	0.7479
0.2	0.38	0.28	0.8857
0.3	0.48	0.17	0.9130
0.32	0.50	0.16	0.9140
0.4	0.62	0.12	0.9170
0.5	0.62	0.10	0.9185



SMOKER LIAR MODEL

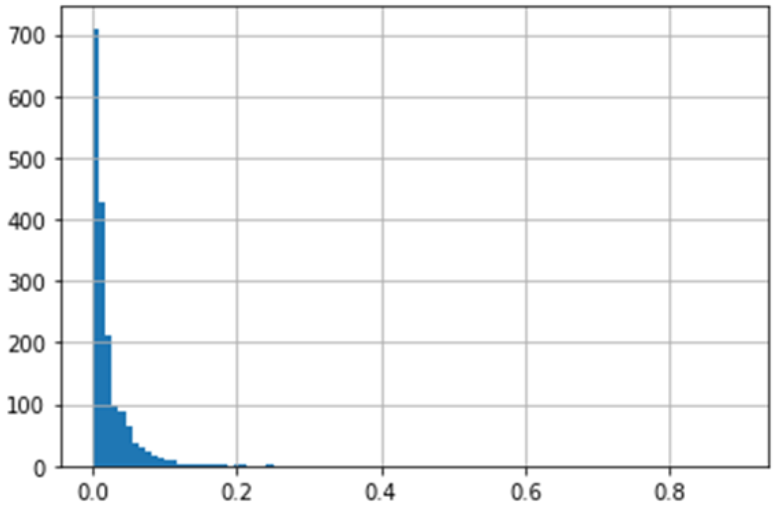
AUC score: 0.73





SMOKER LIAR MODEL

Threshold	Precision	Recall	Accuracy
0.1	0.21	0.16	0.9362
0.2	0.31	0.07	0.9597
0.3	0.60	0.04	0.9614
0.35	0.75	0.04	0.9614
0.38	1.00	0.04	0.9614
0.5	1.00	0.03	0.9614



Next Steps

- Socialize with underwriting and actuarial team for feedback
  - Generating use cases
  - Feature engineering brainstorming
- Determine path for deployment

Thank You!