Machine Learning Applications in Insurance

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Machine learning is ..... 

• Giving computers the ability to learn without being explicitly programmed 
• Designing algorithms that can learn from and make predictions on data 
• When applied for commercial use, this is known as predictive analytics 

• *Machine learning is a buzzword according to the Gartner hype cycle of 2016 and at its peak of inflated expectations*
In the evolution of smart analytics, machine learning has been extensively used for predictive analytic applications.

- **Descriptive analytics**
  - Information
  - Hindsight

- **Predictive analytics**
  - Insight

- **Prescriptive analytics**
  - Optimisation
  - Foresight

**Requirement**
- **Cognitive Computing**
  - IBM Watson
  - Dow Jones DNA tools
  - Swiss Re Life Guide

**Machine Learning:**
- Data Exploration:
- Structured Data:
- Storage:
- Other tools

**Statistics:**
- SAS
- Oracle database

**Tools**
- Data Robot
- Tableau
- Oracle
- Cloud Computer
- R / CRAN Library
- Python / SciKit
Some of the popular machine learning algorithms in use

• At the basic level, based on desired output of a machine-learned system:
  
  − **Classification Algorithms:**
    − Learner assigns unseen inputs to one or more classes.
    − Typically requires *supervised learning* (i.e. labeled data).
    − Examples: Spam filtering where the inputs are email (or other) messages and the classes are "spam" and "not spam".
  
  − **Regression Algorithms:**
    − the outputs are continuous rather than discrete.
    − Typically requires *supervised learning*.
    − Examples: Estimate house prices in a neighborhood.
  
  − **Clustering Algorithms:**
    − for dividing a set of inputs into groups. Unlike in classification, the groups are not known beforehand
    − Typically requires *unsupervised learning* (i.e. no labeled data)
    − Examples: Clustering news articles into topics based on a similarity function
For data scientists, machine learning is an important skill for solving problems using new sources of data
For an organization, an effective data science program requires dedicated strategies targeting four key areas:

**Data**
- Enable scalability, especially for external data
- Target and manage external data sources
- Enable the usage of structured and unstructured internal and external data

**Technology**
- Smart analytics platform for data science initiatives
- Exploit Business Intelligence tools for improved visualization and insight
- Elastic computation and storage
- Cognitive Computing

**People**
- Build and hire new data science talent;
- Integrate the team with the business units
- Talent Radar
- Optimal environment
- Job rotations for business experts and data scientists

**Partners**
- Identify strategic partnerships
- Compliment technical capabilities
- Partner with key data providers
Illustrative examples of Machine Learning applications in the insurance industry

- **Life Insurance Underwriting**
  
  *Predicting Applicant’s Non-smoking Propensity*

- **Property & Casualty Insurance**
  
  *Global Motor Risk Map*
Machine Learning Application to Life Insurance Underwriting

*Predicting Applicant’s Smoking Propensity*

- Business Problem: Can one predict an applicant’s smoking status without fluid-testing?
Developing a “fluid-less” underwriting process based on detecting “smoker propensity” poses several challenges

- **High performance expectation**
  - Sensitivity/specificity of smoker detection solution does not equal or exceed the best medical screening tests thus far.

- **Non-disclosed smoking in insurance applications**
  - Identifying smokers from insurance application is difficult due to large number (up to 50%) of non-disclosed smokers, i.e., actual smokers self-reporting as non-smokers.

- **No smoker-specific profile available to identify smokers**
  - Difficult to detect smokers using “smoker” characteristics in application data.
3-part solution approach is designed to address the challenges of fast underwriting for life insurance policies

1. A Predictive Analytics Model
   - Model designed to predict smokers and non-smokers

2. A Triage-based Underwriting Process
   - Majority of applicants (go through Fast Track process requiring no lab (cotinine) tests for smoking
   - Predicted smokers go through Traditional (business-as-usual) process with lab test required

3. A Cost/Benefit Analysis and Optimization Model
   - Analyzes cost impact of prediction errors (i.e., misclassification of smokers as non-smokers) & savings from fast track with no lab-test for majority of applicants
   - Computes age, gender, and face amount requirements for a client-specific life product with positive NPV

Following slides provide details on the 3-part solution
### Analytics Model: Sample predictors used from internal & external data sources

<table>
<thead>
<tr>
<th>Sample Application Data</th>
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<tbody>
<tr>
<td>Gender</td>
</tr>
<tr>
<td>PlaceOfBirth</td>
</tr>
<tr>
<td>InsuranceAge</td>
</tr>
<tr>
<td>AlcoholAbuseFlag</td>
</tr>
<tr>
<td>Income</td>
</tr>
<tr>
<td>DrugAbuseFlag</td>
</tr>
<tr>
<td>BMI</td>
</tr>
<tr>
<td>BenefitTermLife</td>
</tr>
<tr>
<td>BenefitAmount to Income Ratio</td>
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<td>...</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Sample Data from External Open Sources (CDC, ALA, etc.)</th>
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</thead>
<tbody>
<tr>
<td>Tobacco-related data by State:</td>
</tr>
<tr>
<td>• Tobacco tax</td>
</tr>
<tr>
<td>• Smoking cessation spending per smoker</td>
</tr>
<tr>
<td>• Laws banning smoking in public spaces</td>
</tr>
<tr>
<td>• Number of tobacco retailers per 10K</td>
</tr>
<tr>
<td>• Smoking rates by county</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>US Data from 3rd party vendors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medical Information Bureau (MIB)</td>
</tr>
<tr>
<td>Motor Vehicle Records (MVR)</td>
</tr>
<tr>
<td>Prescription History (Rx)</td>
</tr>
</tbody>
</table>
Analytics Model: Model’s prediction performance is good on several metrics

Performance Metrics Explained

Recall (R):
What percent true-positives in the population are correctly identified?

Precision (P):
What percent predicted positives are indeed true positives?

F-score (F):
Useful metric for skewed class population
\[ F = \frac{2 \times P \times R}{P + R} \]

Area under ROC curve (AUC):
Higher value (closer to 1) indicates good prediction performance

Prediction Model Details

Problem Type: Classification

Machine Learning Techniques used:
• GBM (best performance)
• GLMNET (Logistic regression)
• Random Forest
Triage using predictive analytics model supports fast-track processing for majority of the applicants (> 84%)

Life Insurance Application Details

Self-Declared Smoker

Self-Declared Non-Smoker

Apply Predictive Model

Business as usual (< 16%)

Fast Track (> 84%)

Predicted Smoker

Predicted Non-Smoker

Lab Test Reqd.

Tested Smoker

Tested Non-Smoker

Smoker Rate

Smoker Rate

Non-Smoker Rate

Non-Smoker Rate

Note: Tobacco Usage is only one aspect of the overall risk.

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Cost-Benefit: Calculator computes NPV of life product using predictive model and actuarial data

Prediction Model Results

- Smokers
- Non-Smokers

Cost-Benefit Calculator

Actuarial Data

<table>
<thead>
<tr>
<th>Male PV of Mortality Cost by Smoking Status</th>
<th>Actual Non-Smokers</th>
<th>Actual Smokers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pred. Non-Smkr</td>
<td>Lab-testing savings</td>
<td>Increased Mortality Costs, Lab-testing savings</td>
</tr>
<tr>
<td>Pred. Smkr</td>
<td>Business as usual</td>
<td>Business as usual</td>
</tr>
</tbody>
</table>

- SM PV of Mortality Cost: $1,575, $1,556, $3,642, $8,353, $25,55, $54,03, $116,6, $214,0
- NS PV of Mortality Cost: $816, $826, $1,507, $3,129, $7,615, $23,98, $78,00, $161,2

Nitin Nayak | Digital & Smart Analytics | CIA Annual Meeting
Cost-Benefit: 10-year term life product for applicants below age 55 and face amount < $100K

- For ages below 55, Lab-test Savings > Mortality Costs results in positive NPV
- For ages 55 and beyond, Mortality Costs > Lab-test Savings results in negative NPV

Costs, Savings, and Net Benefit (NPV) displayed by applicant’s Age
(population = 100,000 applicants, product = term life with $100K face amount)

Actuarial Data: Source-LMS US data on PV (Mortality Costs) based on age, insured amount, gender, product term
Cost Assumption: Lab testing cost $55 (does not include parameds)
Note: Revenue impact of fast underwriting process is not included in calculations
Machine Learning Application for Property & Casualty Insurance

Global Motor Risk Map

- Business Problem: Can one predict a geographical area’s motor accident propensity in the absence of relevant statistics?
Challenges in predicting motor accident risk in high-growth markets are several

- Limited Data Availability
  - Available data to analyse motor accident risk in high-growth markets is often limited

- Inherent Bias
  - In-house data is often biased with respect to the overall market due to current positioning of the insurer

- Coarse Granularity Published Data
  - Data published by regulator etc. give only a high-level overview with coarse spatial granularity.
The Global Motor Risk Map can predict car accident risk (frequency and severity) with high spatial granularity

- Swiss Re’s Global Motor Risk map is a predictive model for car accident risk.
- Geographical distribution of risk factors such as weather, road network, traffic or population density with high spatial granularity provides detailed risk prediction.
- Individual risk predictions for frequency and severity lead to a variety of tangible business insights.

<table>
<thead>
<tr>
<th>Input data</th>
<th>Risk predictions</th>
<th>Business insights</th>
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<tbody>
<tr>
<td>Road network</td>
<td></td>
<td><img src="#" alt="Market potential view" /></td>
</tr>
<tr>
<td>Land use</td>
<td>Accident frequency</td>
<td><img src="#" alt="Portfolio steering" /></td>
</tr>
<tr>
<td>Weather</td>
<td>Accident severity</td>
<td><img src="#" alt="Marketing strategy" /></td>
</tr>
<tr>
<td>Night light</td>
<td></td>
<td><img src="#" alt="Performance benchmarking" /></td>
</tr>
<tr>
<td>Population</td>
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<tr>
<td>Elevation</td>
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</tbody>
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Source: GMRM, Swiss Re analysis
Some data statistics

• Road Maps
  – Open street map 250GB
  – North America - 150GB, Europe - 200GB

• Street Segments
  – Germany - 8 Million, USA - 35 Million

• Geographical Grid Cells
  – China >100,000 (10x10km) cells

Satellite Images
  – Precipitation 30GB, Altitude data 30GB
Example: For portfolio steering, GMRM provides tangible insights and suggestions to business.
Some lessons learned...

**The solution**
- Do not stop at the tool level
  - Business value
  - Business Insights
  - Predictions
- Using the right data is more important than the right tool
  - Standard B2B
  - Swiss Re

**The development**
- B2B client differ in number, size and internal diversity
  - B2C
  - B2B
- “Skin in the game” makes service more attractive
  - Swiss Re
  - Information level
  - Financial resilience
  - Client

**The deployment**
- Early-on inclusion of client gives guidance and buy-in
  - Standard B2B
  - Swiss Re
  - Provider
  - Client
- Identify early-on who on the client side will use the service
  - Number of users
  - Level of expertise
  - Work location
  - Available resources
  - Service design
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