Agenda

1. Introduction to Artificial Intelligence and Machine Learning
2. Example Application: Workers’ Compensation Severity Model
3. Example Application: Workers’ Compensation Claim Fraud Identification Model
4. Other Applications of Machine Learning
Introduction to Artificial Intelligence and Machine Learning
What is Artificial Intelligence?

“The theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages.”

- The English Oxford Living Dictionary

<table>
<thead>
<tr>
<th>Computer Vision</th>
<th>Image Recognition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Machine Learning</td>
<td>Natural Language Processing</td>
</tr>
<tr>
<td>Robotics</td>
<td>Automated Speech Recognition</td>
</tr>
</tbody>
</table>
Machine learning is a subset of artificial intelligence that describes systems that can “learn” without human intervention.

The learning is conducted by providing data and a defined objective to the computer, which will train on the data until the objective is reached.
# Machine Learning Considerations

<table>
<thead>
<tr>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Machine learning models can identify complex, non-linear relationships in the data</td>
<td>“Black box” of how model derives results incompatible with business need for intuitive explanation</td>
</tr>
<tr>
<td>Flexible architecture capable of consuming a broad range of data sources</td>
<td>Many models require large amounts of data for sufficient training and validation</td>
</tr>
<tr>
<td>Large range of functional application suitable for the varied needs of insurers</td>
<td>Appropriate application of machine learning can require a much higher degree of knowledge in numerics, programming, and hardware</td>
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</table>
Natural Language Processing is another subset of artificial intelligence that describes the ability of computer systems to approximate a human-level understanding of language.

Natural language processing is used to translate text, summarize large files, and provide sentiment analysis, among other applications.

In Insurance:

Natural language processing is often used in conjunction with machine learning models to extract information from unstructured data.

Common unstructured fields include:
- Claim adjuster notes
- Medical provider notes
- Underwriter notes
- Other self-reported or unstandardized fields
Machine Learning Applications

- **Predicting Claim Cost**
  - Uses claim characteristics to predict ultimate settlement amount
  - Can identify claim characteristics correlated with high losses
  - Can effectively triage claims for more appropriate handling

- **Flagging Fraudulent Claims**
  - Identifies potentially fraudulent claims using claim information
  - Speeds up claim settlement for claims unlikely to be fraudulent, and enables more targeted claims investigation

- **Automated Risk Assessment**
  - Assigns risk tier using data of the party seeking insurance
  - Risk tier and other model output helps underwriter to decide how to underwrite and price the risk
  - Enables more efficient and accurate underwriting
Example Application: Workers’ Compensation Severity Model
Input Data
Workers’ Compensation Claims Data

Structured Data Fields:
- **Demographic data**: Age, sex, marital status, occupation, wage
- **Claim information**: Report lag, indemnity status, attorney involvement, location of injury
- **Injury information**: Injury body part, nature of injury, cause of injury
- **Medical information**: Provider type, CPT/HCPCS codes (procedures performed), NDC codes (drugs administered), ICD codes (diagnosis), treatment factors

Unstructured Data Fields:
- **Medical provider notes**: description of provider/facility, procedures conducted, diagnosis, treatment required (surgery, number of physical therapy visits, prescription for painkillers/opioids)
- **Claim notes**: description of accident and injury details
- **Witness reports**: description of witness testimonies of accident
- **Mental/Physical wellbeing history**: description of preexisting conditions or comorbidities that may impact recovery time (obesity, mental stress, substance abuse, etc)
- **Indemnity status notes**: description of estimated time to return to work
- **State regulations and rules**: description of regulation that relate to medical treatment guidelines and indemnity payments
Severity Model Usage

We run the model using claims data at various points in time of the claims cycle:

- **FNOL**
- **30 days**
- **60 days**
- **120 days**

Time Since Loss

- Severity Model
  - Severity Scores
  - Reason Codes

Iterative evaluation by claims
Benefits to the Insurer

- Severity risk scores and reason codes are used to triage claims, leading to improved outcomes for all parties:
  - Faster return-to-work
  - More efficient claims handling
  - Improved accuracy of case loss reserve estimates
- The reason codes are also used to identify variables correlated with the model’s predictions (e.g. obesity, opioid use)
  - Enables better case management to target actions that reduce impact of these high-risk indicators (e.g. weight management, opioid addiction)
  - Informs adjusters of the potential complexity of the claim for improved assignment
## Factors Affecting Success of a ML Severity Scoring Application

<table>
<thead>
<tr>
<th>Factor</th>
<th>Keys to Success</th>
</tr>
</thead>
</table>
| Quality of data - how accurate is the data? | ● Validate and edit data as necessary  
● Use structured approach to data collection  
● Communicate importance to adjustors       |
| Breadth of data - how detailed is the data? | ● Conduct interviews for in-depth responses  
● Expand the number of fields collected  
● Utilize more existing vendor data  
● Purchase external data sources             |
| Volume of data - how much data is available?| ● Participate in a consortium  
● Operationalize older data                                                              |
| Uptake by staff - how appropriately will staff use the model? | ● Encourage staff to participate in model development  
● Provide adequate training on model                                                              |
Example Application: Workers’ Compensation Claim Fraud Identification Model
A fraud identification model uses similar input data as a severity model, the difference being we seek to feature engineer “fraud indicators” as input for the model.

<table>
<thead>
<tr>
<th>Common Fraud Indicators</th>
<th>Claims Data Needed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inconsistent description of accident</td>
<td>Medical provider report, claimant testimony</td>
</tr>
<tr>
<td>Discrepancy between claimant testimony and witness accounts</td>
<td>Claimant and witness descriptions of accident</td>
</tr>
<tr>
<td>Late reporting of loss</td>
<td>Loss date, report date</td>
</tr>
<tr>
<td>Medical diagnosis is refused</td>
<td>Medical provider report</td>
</tr>
<tr>
<td>No permanent address for claimant or frequent relocation</td>
<td>Claimant demographic details, address</td>
</tr>
<tr>
<td>Claimant files in state other than that of residence or employment</td>
<td>Location of accident, claimant address and claimant employer address</td>
</tr>
<tr>
<td>Accident occurred Monday morning</td>
<td>Loss date and time, medical provider report</td>
</tr>
</tbody>
</table>
Example Claim Fraud Identification Model Development

Step 1: Cluster Data Using Unsupervised Learning

1. Input Data
2. Unsupervised Model
3. Split Data into Clusters
4. Assign Clusters as Fraudulent/Not

Assignment should be based on the fraud indicators in each cluster as well as expert judgment.

Step 2: Detect Fraud in New Claims Using Supervised Learning

1. Data with fraud assignment
2. Supervised Model
3. Fraud Propensity Score Reason Codes

Assignment should be based on the fraud indicators in each cluster as well as expert judgment.
Evaluating the Fraud Model - Confusion Matrix

Confusion Matrices:
- Used to visualize how successfully the model performed in distinguishing between fraudulent vs non-fraudulent claims
- Shows frequency of the following scenarios:
  - A fraudulent claim was predicted as fraudulent (True Positive)
  - A legitimate claim was predicted as fraudulent (False Positive, aka Type I error)
  - A fraudulent claim was predicted as legitimate (False Negative, aka Type II error)
  - A legitimate claim was predicted as legitimate (True Negative)
- Accuracy of the model can be defined as frequency of true positives and true negatives divided by total number of data points
- In the sample scenario presented on the right, both models have the same accuracy...which do we choose?

Model 1

<table>
<thead>
<tr>
<th>Pred \ Actual</th>
<th>Fraud</th>
<th>Not Fraud</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fraud</td>
<td>1,500</td>
<td>980</td>
</tr>
<tr>
<td>Not Fraud</td>
<td>500</td>
<td>97,020</td>
</tr>
</tbody>
</table>

Accuracy: \( \frac{1,500 + 97,020}{100,000} = 98.52\% \)

Model 2

<table>
<thead>
<tr>
<th>Pred \ Actual</th>
<th>Fraud</th>
<th>Not Fraud</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fraud</td>
<td>1,800</td>
<td>1,280</td>
</tr>
<tr>
<td>Not Fraud</td>
<td>200</td>
<td>96,720</td>
</tr>
</tbody>
</table>

Accuracy: \( \frac{1,800 + 96,720}{100,000} = 98.52\% \)
Evaluating the Fraud Model - Cost Matrix

**Cost Matrices:**

- Adds another dimension to model evaluation
- Shows cost to business for each scenario
- Costs can then be used as weights to confusion matrix frequencies to establish which model would incur the least business cost or greatest ROI
- In our sample scenario, we identified that flagging a legitimate claim as fraudulent (Type I error) is more costly to a workers’ compensation insurer than labeling a fraudulent claim as legitimate (Type II error)
  - Consequently, we would use the model that produces less Type I errors (Model 1)

<table>
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<th>Not Fraud</th>
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<tbody>
<tr>
<td>Fraud</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td></td>
<td>Correctly flagged as fraud, stop paying</td>
<td>Save money in short-term, but damaging long-term effects on credibility</td>
</tr>
<tr>
<td>Not Fraud</td>
<td>Medium</td>
<td>Low</td>
</tr>
<tr>
<td></td>
<td>Loss of money due to payments on fraudulent claim, chance to identify as fraudulent later on</td>
<td>Correctly flagged as legitimate, continue paying</td>
</tr>
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Benefits to the Insurer

- Fraud propensity scores allow insurers to more accurately and efficiently identify fraudulent claims
  - Improved bottom line due to nonpayment of fraudulent claims
  - Faster claims handling and investigation
  - Better assignment of claims to SIU (Special Investigations Unit)
  - Decreased likelihood of flagging a legitimate claim
- The reason codes are used to identify variables/indicators correlated with claim fraud
  - Further enables fraud detection
  - Allows for triaging of claims for further investigation
### Factors Affecting Success of a ML Fraud Identifier Application

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● Operationalize older data |
| Uptake by staff - how appropriately will staff use the model? | ● Encourage staff (notably SIU/investigation experts) to participate in model development  
● Provide adequate training on model |
| Fraud indicators - how effective are the fraud indicators in distinguishing claims? | ● Use natural language processing to extract insight from unstructured text (medical provider report, claim adjuster notes)  
● Expand domain knowledge to refine indicators and assign clusters |
Other Applications of Machine Learning
Other Applications

Machine Learning can also be used in the following ways:

- Litigation propensity
- Subrogation likelihood
- Opioid addiction
- Return to work
- Medical to indemnity transition
- Provider scoring
Contacts

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Thank you