Speaker Introductions

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Conflict of Interest

Elizabeth Clements, MBA and Debdipto Misra, MS

Have no real or apparent conflicts of interest to report.
Agenda

• Overview of Geisinger Health
• Why Machine Learning?
• Valuation and Business Model Considerations
• Lessons Learned from Geisinger’s Machine Learning Journey:
  – Text Analytics Use Case
  – Surgical Smoothing Tool Use Case
• Recommendations for Starting a Machine Learning Program
Learning Objectives

• Summarize machine learning, its value to the business, and challenges to consider

• Propose a framework for evaluating machine learning use cases

• Demonstrate the operational and clinical benefits of machine learning in practice
Overview of Geisinger Health
What We Do...

Geisinger Health: is a $7.5B integrated health organization:

- We care for patients
  - 13 hospital campuses
  - 9 surgery centers
  - 216 clinic sites
  - 2,800 providers
  - 30,000 employees

- We provide quality, affordable healthcare coverage
  - 560,000 members
  - 61,000 contracted providers/facilities

- We teach, research and innovate
  - 504 MBS/MD students at GCSoM
  - 475 residents/fellows
  - 900+ active research projects
Geisinger Technology and Analytics

**Vision**

Be an elite IT organization:
- Autonomic systems & infrastructure
- ITIL+
- Level 5 services & skills
- People are visionaries & problem-solvers

**Mission**

- “Make it the best.”

**Values**

- Character matters more than skill
- We are a team
- It is not a zero-sum game
- Discipline
- Honesty
Why Machine Learning?
As Moore’s Law Slows, Machine Learning Grows

Machine Learning

- Statistical mathematics
- Enables humans to “teach” machines
- Continual learning
- Intersects data mining and knowledge discovery
- Branch of Artificial Intelligence (AI)

Source: https://www.intel.com/pressroom/kits/events/moores_law_40th/
Valuating Machine Learning

Management Considerations

- Evaluate multiple measures:
  - Algorithm accuracy
  - Operational improvements
- Move from pockets of innovation to a centralize strategy, but remain flexible
- Complement the data scientist team with:
  - Process engineers
  - Mathematicians
  - Business leaders
  - Project managers/coordinators
Determining the Business Case: A Framework

**Information Capture**
- Capture new data
- Interpret data objects
- Codify, classify, and make new data accessible

**Prediction Automation**
- Advance clinical functions
- Improve the accuracy and productivity of administrative functions

**Judgement Generation**
- Derive new machine knowledge

New observations generate new use cases & discovery
Feedback generated to the machines through task automation
Geisinger’s Journey: Text Analytics

Information Capture
and the Importance of Infrastructure
Why?

Cancer patient sues Geisinger

$75G lawsuit claims illness was left untreated for years

The Boston Globe

$16.7 million award in cancer lawsuit

Verdict based on misread X-ray

Radiologists Settle for $900,000 in Missed Lung Cancer Lawsuit

2004 Medical Malpractice Settlement Report

Radiologists failed to verbally communicate abnormal findings to clinicians. Clinicians failed to follow up on written radiology report in lung cancer case.
20% of total Medicare hospital cost is due to cancer

Close The Loop Project

Patient Care Gaps

Patient Contact
Appointments Made
Clinical Registry
Why Text Analytics?

- **Insightful, detailed pieces of information** describing patient health and patient care **are not captured in standardized forms** or records, but in free-form text fields, notes, or comment sections.

- Notes may be **difficult to search** using traditional “find text”.

- Large-scale text analyses **improve throughput and context**.
• **~200 million notes** in Epic with ~60,000 notes generated per day
• cTAKES, can annotate ~50,000 notes / hour (~**1 million notes in a day**) 
• Annotations are used to extract features, entities, and medical events
Natural Language Processing Pipeline: Overview

- Patient Notes Extraction
- cTAKES Dictionary Annotation
- cTAKES Sentiment Analysis
- Notes Cleansing
- Notes Filtering
- Custom Annotators
Text Analytics Workflow

- **Radiology notes**
  - NLP and Dictionary annotator
    - Annotates with UMLS concept codes
  - Lung nodule Filter annotator
    - Identifies Lung nodule note.

  **Lung nodule note?**
  - YES
    - Negation Annotator
    - Measurement/Lung RADS Calculator
  - NO

- ~ 10 million notes
- ~ 300 thousand notes
- ~ 9.7 million notes
Unified Data Architecture

Governance

Unified Data Architecture
- Data Access and Visualization
  - Data Integration and Enhancement (where appropriate)
  - Access Standards & Security

Enterprise Integrated Data Stores

Operational Reporting Data Stores
- GHP Reporting Database (ODS)
- Rev Cycle Database (Billing)
- Other Departmental Databases

Traditional Sources
- Epic EHR
- Pharmacy
- Financial
- POC
- Laboratory
- Radiology
- Claims

Emerging & Non-Traditional Sources
- Genomics
- Home Devices
- Social Media
- KeyHIE
- Patient Apps

Big Data Environment
- (Structured and Unstructured)
- CDIS (EDW)
- Cogito (Epic Reporting)
- DSS (Cost integrated w/Billing)
Problem Analysis and Challenges
Validation

• Validated by four physician informaticians
• Validation set included 1,096 Notes
• Evaluating for False Positives, False Negatives and Lung RADS score by manual chart review
Performance Measurement

Confusion Matrix

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<th>Actual</th>
<th>Predicted</th>
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<tr>
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<tr>
<td></td>
<td>True Positive</td>
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<tr>
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<td>Yes</td>
<td>False Positive</td>
</tr>
<tr>
<td>No</td>
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</tbody>
</table>

Possible Lung Rad Scores

- Lung-RADS 0: Incomplete.
- Lung-RADS 1: Risk of cancer <1%
- Lung-RADS 2: Benign appearance; nodules are present
- Lung-RADS 3: Risk of cancer 1-2%
- Lung-RADS 4A: Risk of cancer is between 5-15%
- Lung-RADS 4B: Risk of cancer is >15%

Results

- Precision: 0.873
- Recall: 0.947
- F1: 0.908
- Accuracy: 0.912
Key Lessons Learned

✓ Patient Notes untapped source of information
✓ Need proper infrastructure platform like the Unified Data Architecture (UDA)
✓ Analytics based off of big data platform provide granular insights
✓ Self-service model
✓ Proper search and indexing tools (e.g. SOLR, Elastic Search)
Geisinger’s Journey: Surgical Smoothing Tool

Prediction Automation and Trusting the Model
Inpatient Bed Demand Management

• High occupancy rates increase the probability of adverse events
• Several operational challenges exist:
  • Increasing patient volumes
  • Limited capacity
  • Block scheduling
  • Equipment costs
  • 20-25% of OR cases are “addons”
  • Making sense of the data

By predicting an inpatient bed demand score, can we mitigate our risk for adverse events and improve bed management?
Key Considerations in Building the Model

- Characteristics of the training and hold out data sets
- Operational variables – what tribal knowledge do we have?
- Consensus for local definitions of the variables
- Experimentation with variables
- Updates needed over time

### Key Variables

- Day of the week
- Weekend flag
- HolidayFlag
- FullMoonFlag
- Yesterday arrivals (ED, OR, OBS, SORU)
- Yesterday discharges
- Yesterday holds (PACU, ED, CATHLAB)
- Yesterday census (SCU, MED, SURG)
- Yesterday surg outpatient count
- Average census past week
Surgical Smoothing Tool

Decision support tool used to evaluate the impact of:

- Surgical schedule on inpatient bed demand
- Smoothing surgeries to the weekend
- Adding elective cases
- Postponing elective cases
- Decanting elective cases to another hospital location
Operational Use

• Model is run daily at main hospitals to:
  – Predict bed demand for next three days
  – Generate inpatient capacity risk score

• Low ORANGE bed level
  • OR schedule reviewed and case orders arranged to facilitate patient flow

• High ORANGE or RED bed level
  • OR schedule reviewed for opportunities to shift cases to community hospitals
Improving on the Model Over Time

- Early model used Monte Carlo simulation:
  - Retrospective approach
  - Less accurate
  - Little trust in the tool
- Updated to artificial neural network:
  - New observations approach
  - More accurate
  - Improved trust among stakeholders

<table>
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<th>Old Model (Predictive Analytics)</th>
<th>New Model (Machine Learning)</th>
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<tbody>
<tr>
<td><strong>MAE</strong></td>
<td>16.27</td>
<td>9.8</td>
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*Reduced the mean absolute error (MAE) by 40%*
Key Lessons Learned

- Be specific in determining the use case; start small
- Capture pre- and post- measures specific to your use case
- Consciously decide how much you will trust the model; expect mistakes
- Partner closely with the business
- Clearly define who will manage the workflow and the model
- Revisit the model for refinement over time
Machine Learning Recommendations

Define a simple business case
- Abundance of data
- Repetitive or ruminal tasks
- Common/frequent problems

Make key decisions about the model
- Variable definition
- Mistakes should happen
- Iterate on the design
- Level of human intervention

Encourage collaboration
- Mathematicians to support analytics
- Business/clinical support for workflow and validation

Ensure a solid technological foundation
- Data lake (collection of storage instances of various data assets)
- Self-Service
- Build a solution around your use case
Questions

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