2020 VIRTUAL ANNUAL MEETING & EXHIBIT

OCTOBER 26–29, 2020
Session 1A: Recent Advances in Healthcare Analytics

Moderator: Emiliano A. Valdez
Presenters: Guojun Gan, Gary Gau, and Dave Liner

Monday, October 26, 2020
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Session 1A: Recent Advances in Healthcare Analytics

Guojun Gan

October 26, 2020
Analysis of Prescription Drug Utilization with Beta Regression Models

Joint work with Emiliano Valdez

• Background
• Dataset
• Model
• Results
The pharmaceutical industry

• The generics account for 89% of prescriptions dispensed but only 26% of total drug costs in the U.S. (Association for Accessible Medicines)

• Prescription drug spending in the U.S. increased 2.5% to $335.0 billion in 2018, faster than the 1.4% growth in 2017 (National Health Expenditure fact sheet)
Previous work

- Behavioral intension models to examine the decision to purchase generic prescription drugs
- Psychiatrists' decision making between generic and branded antipsychotics
- Experiences of implementing generic medicine policy in eight countries, including the U.S.
- Survey data was used to study the behavior of the patients and physicians
Our work

• To investigate the variations of the brand name drug claims rates in different areas of the U.S.

• Since rates are values in the interval (0,1), the Beta regression model is most suitable where covariates can be introduced to account for heterogeneity.

• A public dataset called the Part D Prescriber Public Use File (PUF) from the Centers for Medicare & Medicaid Services (CMS) and another public dataset called Individual Income Tax Statistics from the IRS (Internal Revenue Service) were used.
The datasets

• The 2016 Part D Prescriber Summary Table (The file name is PartD_Prescriber_PUF_NPI_16.txt)
  • contains 1,131,550 records and 84 variables.
  • contains average ages and average risk scores of the beneficiaries. The average risk scores are average HCC (Hierarchical Condition Category) risk scores

• The 2016 individual income tax statistics by zip codes (The file name is 16zpallagi.csv)
  • contains 29,874 records, each of which is described by 144 variables
  • contains information about the number of returns and the amount of returns in different categories.
Data preprocessing

• The data was aggregated to some customized level between the state level and the zip code level
  • The brand name drug claim rate exhibits variations within individual states.
  • The U.S. has only 50 states and aggregating the data to the state level produces only 50 data points.
  • The dataset contains about 20,000 different zip codes. Aggregating the data to the zip code level will produce about 20,000 data points. This will cause challenges in modeling the spatial effects as a large number of sites requires lots of parameters.
  • Some zip codes do not correspond to geographical areas but large volume customers or post office boxes.
  • Aggregating the data to the zip level produces highly volatile brand name drug claims rates. That is, the rates are highly volatile between zip codes.
Summary of the aggregated data

Figure 2: Distributions of the brand name drug claim rates. White triangles mean that data are not available in these areas.
Training and test data

(a) The training set.  
(b) The test set.

Figure 5: The distribution of the brand name drug claim rates for the training and test sets.
The Beta distribution

The density function of the Beta distribution is typically defined as (Klugman et al., 2012):

\[
f(y; p, q) = \frac{\Gamma(p + q)}{\Gamma(p)\Gamma(q)} y^{p-1}(1 - y)^{q-1}, \quad 0 < y < 1,
\]

where \( p > 0 \) and \( q > 0 \) are shape parameters. The Beta distribution defined in Equation (1) has been reparameterized by using its mean and dispersion as parameters.

\[
f(y; \mu, \phi) = \frac{\Gamma(\phi)}{\Gamma(\mu\phi)\Gamma((1 - \mu)\phi)} y^{\mu\phi - 1}(1 - y)^{(1 - \mu)\phi - 1}, \quad 0 < y < 1,
\]

where \( 0 < \mu < 1 \) and \( \phi > 0 \). The shape parameters can be obtained from the mean and the dispersion as follows: \( p = \phi\mu \) and \( q = \phi(1 - \mu) \).
Beta regression models

The basic Beta regression model is described as follows. Suppose that we have $n$ observations. For $i = 1, 2, \ldots, n$, let $x_i = (x_{i1}, x_{i2}, \ldots, x_{ik})^T$ and $y_i$ be the vector of $k$ regressors and the response in the $i$th case, respectively. The responses $y_1, y_2, \ldots, y_n$ are assumed to form a random sample such as

$$y_i \sim \text{Beta}(\mu_i, \phi).$$

The mean $\mu_i$ is linked to the regressors as follows:

$$g(\mu_i) = \eta_i = x_i^T \beta,$$

where $g(\cdot)$ is the link function and $\beta = (\beta_1, \beta_2, \ldots, \beta_k)^T$ is the vector of regression coefficients.
Beta regression models

The four models described in Section 4 can be formulated as Bayesian hierarchical models. For example, the BetaBYM model can be expressed as

\[ y_i | \eta_i \sim \text{Beta}(g^{-1}(\eta_i), \phi), \]  

\[ \eta_i = x_i^T \beta + u_i + v_i, \]  

\[ v_i | \psi_1 \sim N(0, \psi_1^{-1}), \]  

\[ u | \psi_2 \sim N(0, \psi_2^{-1}Q^{-1}), \]  

\[ \psi \sim \pi(\psi), \]  

where \( \pi(\cdot) \) denotes a prior distribution for the two hyperparameters \( \psi_1 \) and \( \psi_2 \). Common choices for the prior distribution of \( \psi \) include independent gamma distributions.
Table 3: Description of the selected covariates.

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>avgscore</td>
<td>Average risk score</td>
</tr>
<tr>
<td>VITA</td>
<td>Number of volunteer income tax assistance (VITA) prepared returns</td>
</tr>
<tr>
<td>A00900</td>
<td>Business or professional net income (less loss) amount</td>
</tr>
<tr>
<td>A02300</td>
<td>Unemployment compensation amount</td>
</tr>
<tr>
<td>A03150</td>
<td>Individual retirement arrangement payments amount</td>
</tr>
<tr>
<td>A03230</td>
<td>Tuition and fees deduction amount</td>
</tr>
<tr>
<td>A18450</td>
<td>State and local general sales tax amount</td>
</tr>
<tr>
<td>A18800</td>
<td>Personal property taxes amount</td>
</tr>
<tr>
<td>A07230</td>
<td>Nonrefundable education credit amount</td>
</tr>
<tr>
<td>A85770</td>
<td>Total premium tax credit amount</td>
</tr>
<tr>
<td>A11070</td>
<td>Additional child tax credit amount</td>
</tr>
<tr>
<td>A11902</td>
<td>Overpayments refunded amount</td>
</tr>
</tbody>
</table>
Results based on training set

Table 4: In-sample performance of the models with different link functions.

<table>
<thead>
<tr>
<th>Model</th>
<th>Logit</th>
<th>Probit</th>
<th>Loglog</th>
<th>Cloglog</th>
<th>Cauchy</th>
</tr>
</thead>
<tbody>
<tr>
<td>BetaReg</td>
<td>-2103.82</td>
<td>-2102.92</td>
<td>-2101.53</td>
<td>-2104.36</td>
<td>-2109.25</td>
</tr>
<tr>
<td>BetaRE</td>
<td>-2103.60</td>
<td>-2102.20</td>
<td>-2100.60</td>
<td>-2104.10</td>
<td>-2109.79</td>
</tr>
<tr>
<td>BetaBesag</td>
<td>-2105.79</td>
<td>-2109.89</td>
<td>-2109.58</td>
<td>-2107.41</td>
<td>-2114.87</td>
</tr>
<tr>
<td>BetaBYM</td>
<td>-2116.93</td>
<td>-2115.13</td>
<td>-2112.55</td>
<td>-2118.06</td>
<td><strong>2132.92</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>DIC</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>BetaReg</td>
<td>-2070.47</td>
<td>-2070.84</td>
<td>-2071.36</td>
<td>-2069.72</td>
<td>-2062.49</td>
</tr>
<tr>
<td>BetaRE</td>
<td>-2070.60</td>
<td>-2071.07</td>
<td>-2071.56</td>
<td>-2069.88</td>
<td>-2063.02</td>
</tr>
<tr>
<td>BetaBesag</td>
<td>-2077.25</td>
<td>-2081.93</td>
<td>-2083.42</td>
<td>-2077.41</td>
<td>-2069.28</td>
</tr>
<tr>
<td>BetaBYM</td>
<td>-2089.08</td>
<td>-2091.05</td>
<td><strong>2091.60</strong></td>
<td>-2088.89</td>
<td>-2087.56</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>WAIC</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>BetaReg</td>
<td>-2070.47</td>
<td>-2070.84</td>
<td>-2071.36</td>
<td>-2069.72</td>
<td>-2062.49</td>
</tr>
<tr>
<td>BetaRE</td>
<td>-2070.60</td>
<td>-2071.07</td>
<td>-2071.56</td>
<td>-2069.88</td>
<td>-2063.02</td>
</tr>
<tr>
<td>BetaBesag</td>
<td>-2077.25</td>
<td>-2081.93</td>
<td>-2083.42</td>
<td>-2077.41</td>
<td>-2069.28</td>
</tr>
<tr>
<td>BetaBYM</td>
<td>-2089.08</td>
<td>-2091.05</td>
<td><strong>2091.60</strong></td>
<td>-2088.89</td>
<td>-2087.56</td>
</tr>
</tbody>
</table>
Results based on test set

Table 5: Out-of-sample performance of the models with different link functions.

<table>
<thead>
<tr>
<th>Model</th>
<th>Logit</th>
<th>Probit</th>
<th>Loglog</th>
<th>Cloglog</th>
<th>Cauchy</th>
</tr>
</thead>
<tbody>
<tr>
<td>BetaReg</td>
<td>0.42846</td>
<td>0.42810</td>
<td>0.42749</td>
<td>0.42801</td>
<td>0.42138</td>
</tr>
<tr>
<td>BetaRE</td>
<td>0.42834</td>
<td>0.42790</td>
<td>0.42733</td>
<td>0.42786</td>
<td>0.42126</td>
</tr>
<tr>
<td>BetaBesag</td>
<td>0.45289</td>
<td>0.46855</td>
<td>0.47168</td>
<td>0.45622</td>
<td>0.44610</td>
</tr>
<tr>
<td>BetaBYM</td>
<td>0.48595</td>
<td>0.48954</td>
<td><strong>0.49127</strong></td>
<td>0.48584</td>
<td>0.47814</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>RSE</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>BetaReg</td>
<td>0.01380</td>
<td>0.01376</td>
<td>0.01371</td>
<td>0.01383</td>
<td>0.01412</td>
</tr>
<tr>
<td>BetaRE</td>
<td>0.01380</td>
<td>0.01376</td>
<td>0.01371</td>
<td>0.01383</td>
<td>0.01413</td>
</tr>
<tr>
<td>BetaBesag</td>
<td>0.01364</td>
<td>0.01352</td>
<td>0.01342</td>
<td>0.01367</td>
<td>0.01412</td>
</tr>
<tr>
<td>BetaBYM</td>
<td>0.01359</td>
<td>0.01352</td>
<td><strong>0.01340</strong></td>
<td>0.01367</td>
<td>0.01445</td>
</tr>
</tbody>
</table>
Summary

• The results show that modeling the spatial effect improves the performance of the Beta regression model.

• Including unstructured random effects in the model only improve the performance marginally.

• These models can be used to update an insured's risk score in a risk adjustment model.

• Healthcare actuaries can incorporate the geographic variation in their models used to select preferred providers.
Healthcare Integrated Profitability Analysis

Gary Gau

10/26/2020
Agenda

• Background
• ACA Market
• Post-Acute Care Market
• Readmission
• Research Objectives
• Appendix: Technologies and Tools
Background

• The industry is looking for high-performance risk models using advanced predictive modeling and data mining techniques to quantify the risk and to identify new opportunities.

• The business model is moving from a risk selection model to a risk management model.

• The healthcare insurance environment will continue to become a more competitive and customer-oriented business.

• The universal approach will not satisfy all customers, especially when they will have increased freedom of choice in purchasing health coverage.

• To proactively anticipate potential medical needs for all members and to be able to provide appropriate interventions before certain medical conditions develop or complications surface for these members.

• Companies are moving from a health insurance company to a health solution company.
Gross Margin = (Premium + Transfer + CSR + Risk Corridor\(^*\) + Reinsurance\(^*\)) – Paid Claim Liability

Transfer: risk adjustment zero sum money transfer
CSR: cost-sharing reduction for Silver variants
*: temporary programs
2014 Number of HCCs - Adult

Members with conditions subject to risk adjustment are considered more favorable than members without such conditions.

<table>
<thead>
<tr>
<th>Number of HCC</th>
<th>Exposure Distribution</th>
<th>Average Risk Score</th>
<th>Paid Distribution</th>
<th>Premium</th>
<th>Transfer</th>
<th>CSR</th>
<th>Reinsurance</th>
<th>Gross Margin</th>
<th>Gross Margin PMPM</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>71.68%</td>
<td>0.58</td>
<td>23.06%</td>
<td>$1,198,652,385</td>
<td>-$617,116,866</td>
<td>$30,175,677</td>
<td>$16,629,757</td>
<td>$183,748,747</td>
<td>$81</td>
</tr>
<tr>
<td>1</td>
<td>19.96%</td>
<td>3.36</td>
<td>29.81%</td>
<td>$396,875,840</td>
<td>$188,763,994</td>
<td>$31,722,268</td>
<td>$56,191,527</td>
<td>$64,040,989</td>
<td>$101</td>
</tr>
<tr>
<td>2</td>
<td>5.44%</td>
<td>7.58</td>
<td>17.21%</td>
<td>$116,955,664</td>
<td>$214,539,542</td>
<td>$17,860,875</td>
<td>$58,084,912</td>
<td>$29,875,605</td>
<td>$173</td>
</tr>
<tr>
<td>3</td>
<td>1.67%</td>
<td>13.73</td>
<td>9.58%</td>
<td>$37,922,445</td>
<td>$141,159,724</td>
<td>$10,241,526</td>
<td>$45,436,877</td>
<td>$11,558,757</td>
<td>$218</td>
</tr>
<tr>
<td>4+</td>
<td>1.25%</td>
<td>36.91</td>
<td>20.33%</td>
<td>$29,040,363</td>
<td>$319,723,827</td>
<td>$17,685,719</td>
<td>$150,598,734</td>
<td>-$10,878,078</td>
<td>-$275</td>
</tr>
</tbody>
</table>
## 2014 Unfavorable Conditions for Adults

<table>
<thead>
<tr>
<th>Category</th>
<th>Description</th>
<th>Member</th>
<th>Gross Margin</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>HHS_HCC001</td>
<td>HIV/AIDS</td>
<td>1,233</td>
<td>-7,214,873</td>
<td>-5,851</td>
</tr>
<tr>
<td>G18</td>
<td>Completed Pregnancy With Major Complications (207); Completed Pregnancy With Complications (208); Completed Pregnancy with No or Minor Complications (209)</td>
<td>3,748</td>
<td>-6,159,960</td>
<td>-1,644</td>
</tr>
<tr>
<td>HHS_HCC037</td>
<td>Chronic Hepatitis</td>
<td>822</td>
<td>-5,650,300</td>
<td>-6,876</td>
</tr>
<tr>
<td>HHS_HCC036</td>
<td>Cirrhosis of Liver</td>
<td>194</td>
<td>-2,699,701</td>
<td>-13,938</td>
</tr>
<tr>
<td>HHS_HCC118</td>
<td>Multiple Sclerosis</td>
<td>439</td>
<td>-2,470,748</td>
<td>-5,626</td>
</tr>
<tr>
<td>HHS_HCC048</td>
<td>Inflammatory Bowel Disease</td>
<td>1,262</td>
<td>-1,830,734</td>
<td>-1,451</td>
</tr>
<tr>
<td>HHS_HCC035</td>
<td>End-Stage Liver Disease</td>
<td>113</td>
<td>-1,462,945</td>
<td>-12,928</td>
</tr>
<tr>
<td>HHS_HCC113</td>
<td>Cerebral Palsy, Except Quadriplegic</td>
<td>40</td>
<td>-224,119</td>
<td>-5,589</td>
</tr>
<tr>
<td>HHS_HCC131</td>
<td>Acute Myocardial Infarction</td>
<td>109</td>
<td>-149,551</td>
<td>-1,375</td>
</tr>
<tr>
<td>HHS_HCC114</td>
<td>Spina Bifida and Other Brain/Spinal/Nervous System Congenital Anomalies</td>
<td>39</td>
<td>-142,496</td>
<td>-3,682</td>
</tr>
<tr>
<td>HHS_HCC066</td>
<td>Hemophilia</td>
<td>8</td>
<td>-126,415</td>
<td>-16,633</td>
</tr>
</tbody>
</table>
Post-Acute Care (PAC) Market
Medical Loss Ratio (MLR)

to proactively anticipate potential medical needs for all members and to be able to provide appropriate interventions before certain medical conditions develop or complications surface for these members.

to select the right members for the right interventions to increase the risk score or quality score.
Patient Journey

How long is dad here?
Can he go home?
What is the right level of care for him?
Readmission
All Cause Readmission

- Anchor Acute discharge date
- Next Acute Admit date

30 days

Acute

30 days

Acute
Standard Readmission (PAC)

within 30 days

Anchor Acute discharge date

Next Acute Admit date

3 days

within 30 days
Research Objectives

• **Targeted Product Design and Marketing**: to sell the right product to the right people at the right time for the right price at the micro level

• **Revenue Growth**: to select the right members for the right interventions to increase the risk and quality scores

• **Cost Reduction**: It is extremely important to provide the best quality of care utilizing the most efficient approach for these members

• **Risk Adjustment**: to quantify the risk and to identify opportunities under the risk adjustment

• **Risk Optimization**: to coordinate cross-functional strategies and to identify optimized solutions
  o For example, product and network composition

• **Analytical Competitor**: to move from an analytical company to an analytical competitor
Integrated Profitability Analysis

Profitability/Pricing

Transfer

Quality

Marking/Sales

Risk

Care
Appendix: Technologies and Tools
Predictive Modeling Methodology

1. Define the business problem.
2. Translate business problems into predictive modeling problems.
3. Select appropriate data.
4. Get to know the data.
5. Create a model set.
6. Fix problems with the data.
7. Transform the data.
8. Build models.
10. Deploy models.
11. Assess results.
Product Development in Healthcare Analytics

Dave Liner
Principal & Consulting Actuary
Milliman Curv
What is Curv®?

- Uses de-identified Rx data to calculate a mortality score for a population
- Allows insight into mortality well before experience becomes credible
- No HIPAA authorization required – no PHI
Curv Data Flow

Insurance Company

- Prospect Data
  - Unique ID
  - Curv Score

3rd Party Tokenizer

- Token

Milliman Curv®

Predictive Model

- System ID
  - Rx Data

Retail Pharmacies

- Token
  - Rx Data

Rx Retail De-identified Aggregators
How does Curv stratify groups into risk score ranges?

![Graph showing stratification of risk scores into ranges](image-url)
Curv effectively predicts group LTD morbidity

Client Study of 8,300 Groups
Retrospective Study Conclusions

- Curv is a better predictor than the traditional rating methods
  - Lift curves show that Curv can stratify both mortality and morbidity risk
  - Bidding simulation shows positive gains when using Curv in the marketplace

- Potential value:

<table>
<thead>
<tr>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>A. Gain per $1000 of premium sold</td>
<td>$173.21</td>
</tr>
<tr>
<td>B. Gain per $1000 of premium quoted (A x 10%)</td>
<td>$17.32</td>
</tr>
<tr>
<td>C. Curv per hit fee</td>
<td>$2.00</td>
</tr>
<tr>
<td>D. Curv cost (per $1000 of premium quoted)</td>
<td>$3.13</td>
</tr>
<tr>
<td>E. Benefit to Cost (B ÷ D)</td>
<td>5.5 to 1</td>
</tr>
</tbody>
</table>
Milliman HealthIO
HealthIO Process

- Predict the risk of diabetes and/or hypertension at individual level in the next six to twelve months
- Utilize recent 24 months of medical claims, pharmacy claims, and enrollment history
- Stratify the population using the score above for risk of developing specific conditions
- Enroll elevated risk individuals in a self-administered biometric monitoring program
- Provide alerts to support network of family and healthcare professionals when biometric readings warrant
- Capture and report biometric data for use by clinical staff for necessary intervention
- Improve the prediction algorithm
Step 1: Condition Prediction

- Determine likelihood of a condition diagnosis in the next 6-12 months
  - ICD10 codes vary by condition (e.g., Diabetes Type 2: E11*; CAD: I25*)
- Lookback period is 24 months
- Output includes a member absolute risk score, relative risk score, variable importance
Input Variables

- Demographic: Gender, Age, MSA
- Diagnosis: All ICD codes
- Drugs: All NDCs by Therapeutic Class
- Procedures: All ICD, HCPCS, CPT Procedures

- 6,000+ variables
- Ensemble decision-tree algorithm - gradient boosted machine (GBM)
- Captures non-linear variable relationships and interactions

- Data Quality/Exclusion Criteria (Age, first claim, invalid codes)
Receiver Operating Characteristic Area Under the Curve (AUC)

- Compares tradeoffs between detection (True Positive) and false alarm rate (False Positive)
- 1.00 perfectly predicts with no false positives, 0.50 is the same as a coin flip

Source: CivitasLearning
AUC Comparison

OK

Better

Best
Sample Performance

- Diabetes
  - 22% sensitivity; 98.1% specificity; 95.5% accuracy; 30.5% precision
  - Area Under the Curve (AUC): 0.89
  - Example: 50,000 member population, at 90% threshold, 430 true positives and 43 false positives

- Hypertension
  - 21.8% sensitivity; 99.3% specificity; 99.1% accuracy
  - Area Under the Curve (AUC): 0.92
Step 2: Self-administered biometric monitoring program

- Blood Pressure
- Heart Rate
- SpO2
- Weight
- Blood Sugar
- Adherence to prescription
- Hydration
- Mood
- Pain
- Digestion
- Visualization
- Alerts & Notifications
- Reminders
- Care coordinators
- Advocates/Concierge
- Primary care
- Family & friends
- Risk analysis & quantification
- Predictive analytics
- Population dashboards
### Key Preventive Scenarios

**What are the Key Value Drivers?**

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Payer Value</th>
</tr>
</thead>
</table>
| **Chronic Conditions** – Significant Driver of Cost | • **Stratify** members/patients based on Risk of developing Chronic Conditions*  
• **Empower** them to Manage Risk and Avoid Onset of Condition  
• **Involve** Family and Caregivers in CC Management and Preventive Journey |
| **ER/UR Overuse** – Unplanned Cost Spikes, PCP Underutilized | • **Inform** and Enable primary care and loved ones of outcomes/adherence  
• **Alert** Caregivers to impending emergencies before they happen  
• **Avoid** ER/UR Visits via examination of longitudinal Health Data |
| **Poor Health Engagement** – Low Awareness,Declining Health | • **Engage**, preventively educate members/patients in their Vitals, Risk Factors  
• **Increase** energy and productivity  
• **Reduce** Absenteeism |
| **Poor Health Literacy** – Lack of Individualized Awareness and Rising Risks | • **Educate** members to manage their own Health Care  
• **Monitor** ongoing Risk Scores – and communicate/educate appropriately  
• **Enable** Individualized Communication & Incentives, Health Ecosystem |

* Cost of T2 Diabetes > $500 PEPM following Diagnosis
Project Nightingale
Paging Nurse Google
The tech giant is teaming with Ascension on an ambitious project to crunch patient data for treatment and administrative purposes.

1. Patient checks into hospital, doctor’s office or senior care center.

2. Doctors/nurses examine the patient, input data into computers.

3. Data instantly flows to Google’s ‘Project Nightingale’ system. The system may suggest the following outcomes, among others:

   - Treatment plans, suggests tests, flags unusual deviations in care.
   - Replacement or addition of doctors to patient’s team.
   - Additional enforcement of narcotics policies.
   - Ascension may bill more or for different procedures.

Data that is shared includes:
- Name
- Date of Birth
- Address
- Family members
- Allergies
- Immunizations

Source: the companies

Source: https://www.wsj.com/articles/google-s-secret-project-nightingale-gathers-personal-health-data-on-millions-of-americans-11573496790
Thank you
Questions?
Thank you!