ESTIMATING THE FINANCIAL VALUE OF WOUNDS FROM THE BOTTOM-UP

OPEN WOUND RESEARCH

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Introduction

Estimating the financial value of treating patients with chronic wounds is important for stakeholders in the wound care ecosystem. Current methods take a top-down or macro-economic approach, with limited usefulness at the microeconomic level. These top-down approaches also ignore patient heterogeneity, which leads to a milieu of inferential problems.

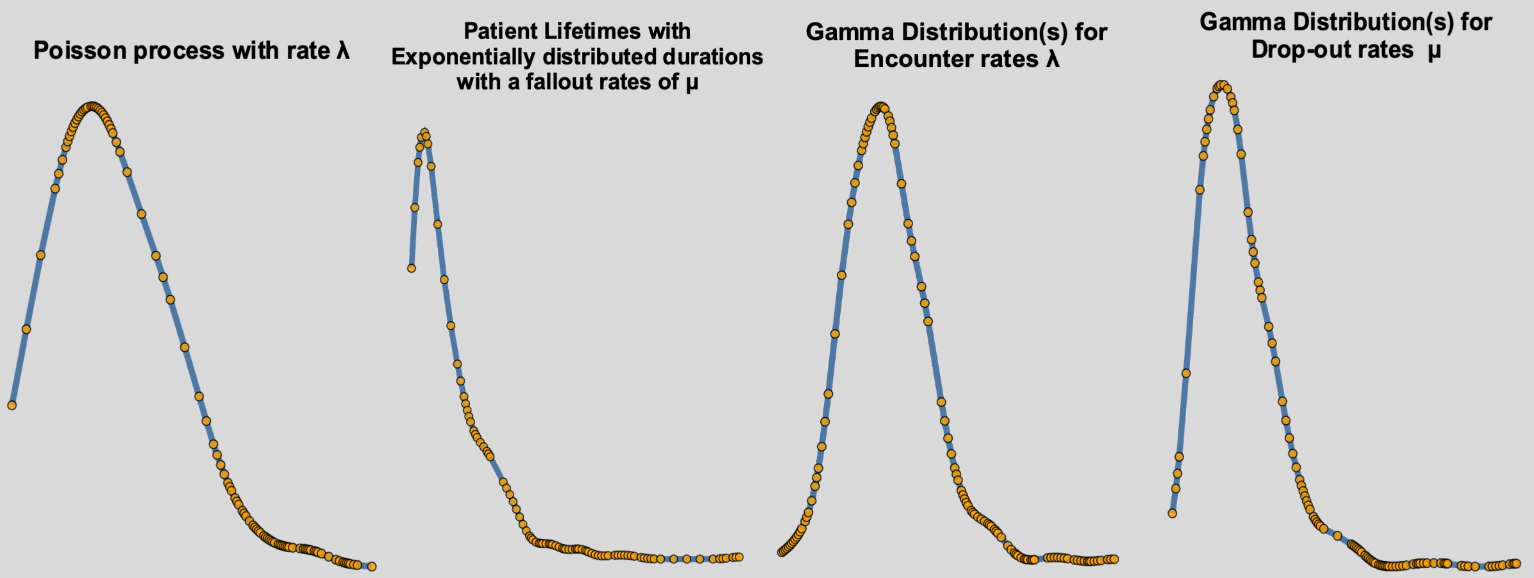
We propose the use of a probabilistic latent attribution model, which requires only transactional data and uses stochastic processes to account for patient heterogeneity, at the microeconomic (patient) level. Given that the estimates are provided at the patient level, it becomes trivial to aggregate the forecasts to arrive at cohort level metrics of interest.

Models such as these will be necessary as major payers shift their payment methodologies to value-based care. To wit, CMS, in its 2021 Strategy Refresh, stated explicitly that it wants all Medicare and the vast majority of Medicaid beneficiaries to be in a care relationship with accountability for quality and total cost of care by 2030.

The Model

The model makes the following assumptions about the patient encounter and drop-out process:

- When still treating, the patient generates encounters according to a Poisson process with rate λ
- Each patients treats for a lifetime which has an exponentially distributed duration with a fallout rate of μ
- The encounter rate λ for the different patients is distributed according to a gamma distribution across the population of patients
- The drop-out rates μ are distributed according to different gamma distributions across patients
- Encounter rates λ and fallout rate μ distributed independently of each other

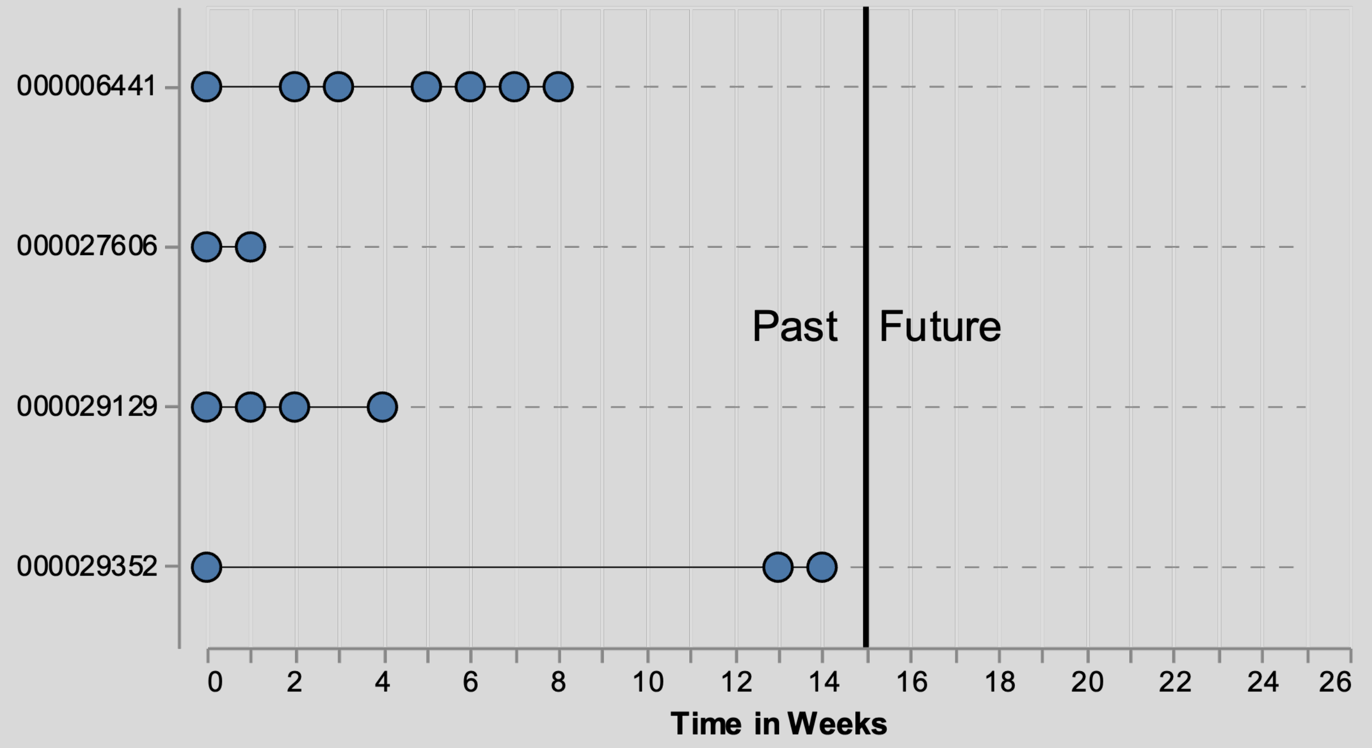


THE ANALYTICAL WORKFLOW → → → → → → →

Patient Lifetimes

- Lifetimes are the linear representations of patient encounters
- They consist of observed and unobserved encounters, with observed encounters in the past and unobserved encounters in the future
- Patients generate encounters at different rates – some patients are regular, some irregular, some regular at first and then irregular
- This makes it difficult to say with absolute certainty whether a patient will treat in the future
- Instead of being deterministic, we must acknowledge uncertainty and think probabilistically, and infer a probability that a patient will have an encounter at some timepoint in the future

Examples of the Lifetimes of Patients



Cohorting

- Cohorts are a group of patients that began treatment in the same epoch (e.g. a calendar month)
- This places patients in a group where their membership never changes
- This allows for tracking of behavior of the cohort over time
- And allows for comparison of different heterogenous cohorts over a common and normalized timescale

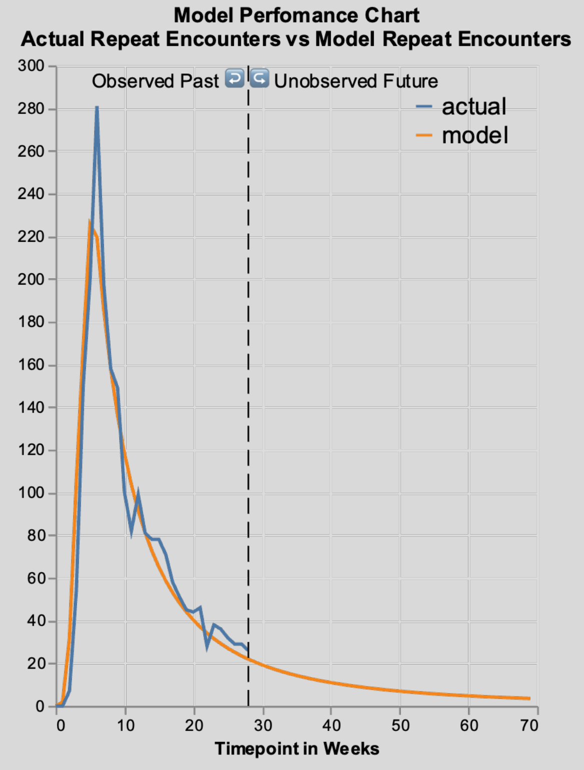
1. Obtain transactional data, then cohort by time

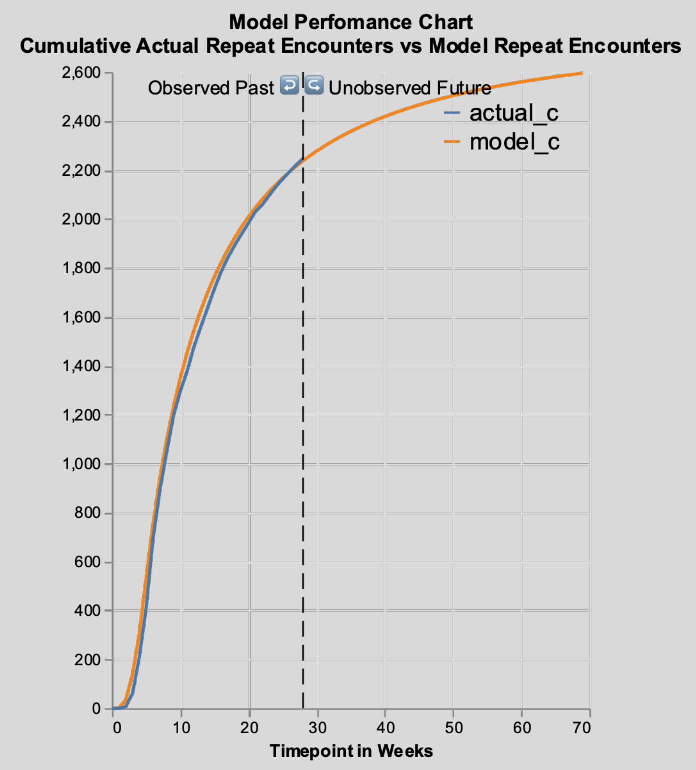
Cohort Month	Patient ID	Date	Payment
May-22	6441	2022-05-17	81.53
May-22	6441	2022-05-31	43.93
May-22	6441	2022-06-07	43.93
May-22	6441	2022-06-21	43.93
May-22	6441	2022-06-28	43.93
May-22	6441	2022-07-05	43.48
May-22	6441	2022-07-12	43.48
May-22	27606	2022-05-26	59.41
May-22	27606	2022-05-31	66.27
May-22	27606	2022-06-02	96.63
May-22	29129	2022-05-27	123.4
May-22	29129	2022-06-03	63.23
May-22	29129	2022-06-10	63.23
May-22	29129	2022-06-24	55.08
May-22	29352	2022-05-26	37.93
May-22	29352	2022-08-26	49.53
May-22	29352	2022-09-02	37.55

2. Generate RFM Summary & Train Model

Patient ID	Frequency	Recency	T
6441	6	8	34
24117	5	10	36
25570	4	4	33
27287	3	7	34
27481	4	5	33
27606	1	1	33
28996	4	4	32
28997	2	2	32
29049	3	10	33
29081	3	3	25
29087	5	5	32
29103	4	4	33
29109	2	23	34
29118	1	6	21
29119	1	1	22
29125	2	3	27
29129	3	4	33

3. Validate the Model





4. Generate Patient Level Predictions

Patient ID	Probability still Treating	Predicted Conditional Encounters	Predicted Unconditional Encounters	Estimated Average Revenue	Predicted Patient Lifetime Value
12669	0.3%	0.0	0.0	$ 38.48	$ 0.82
23815	0.0%	0.0	0.0	$ 75.63	$ 0.07
24618	1.4%	0.1	0.1	$ 54.10	$ 5.89
26966	5.0%	0.3	0.4	$ 258.29	$ 105.52
27492	93.4%	5.6	6.9	$ 53.85	$ 372.29
29672	0.1%	0.0	0.0	$ 75.63	$ 0.35
30153	1.9%	0.1	0.2	$ 55.00	$ 8.37
30174	1.6%	0.1	0.1	$ 49.16	$ 6.14
30275	0.3%	0.0	0.0	$ 59.34	$ 1.14
30280	0.0%	0.0	0.0	$ 75.63	$ 0.07
30287	0.2%	0.0	0.0	$ 53.75	$ 0.79
30288	23.9%	1.5	1.9	$ 37.18	$ 69.61
30393	42.8%	2.7	3.3	$ 61.26	$ 203.52
30395	0.2%	0.0	0.0	$ 43.61	$ 0.64

5. Generate Cohort Level Predictions using Patient Level Predictions

Cohort Metric	Value
Predicted Future still Treating Patients week 26	95
Predicted Future Encounters up to week 26	590
Predicted Future Encounters up to Infinity	731
Predicted Future Lifetime Value of Cohort	$ 45,835

- Not only can one aggregate Patient Level Predictions at the global level, one can also append individual level data, such as demographic, clinical or other data, and aggregate at those levels as well.
- Comparisons can be made within and between cohorts at global or sub-global levels.

3. Utilize the Predictions to make decisions

- A practice is approached by a payer who offers a population value- based arrangement. For the cohort above, the payer offers $40,000 for 26 weeks of services. Using the Predicted Future Value of the the Cohort of $45,835, the Practice can refuse the offer, and counter appropriately
- A wound care product supplier wants to understand which patients among its patient base will require the most product in the future, for logistical and support purposes. The supplier can use the patient level predictions (merged with location data) of Predicted Conditional/Unconditional encounters to proactively allocate resources to meet future demand.
- A home-health agency wants to allocate wound care nurses to manage its value-based contract. Management can use the patient-level predictions of Predicted Conditional/Unconditional encounters to identify patients most likely to require the most wound-care services. This allows for a financial risk-stratification, in conjunction with clinical risk-stratification.