Deep Care Management at Duke
Lessons in Using ML in a Medicare Population

Erich S. Huang, MD, PhD
erich.huang@duke.edu
Betty C. 65 years old. History of myocardial infarction, status post CABG, congestive heart failure, drug dependency

Admitted via Emergency Department with chest pain and pulmonary edema

Betty C. Discharged and lost to follow-up
Betty C. is *lost in the shuffle*
Medical tradition
Duke Connected Care
Duke Connected Care
Medicare Shared Savings Program Track 3
Medicare Shared Savings Program Track 3

- Exceed: ACO shares 40%-75% of losses based on quality performance
- Save: ACO shares up to 75% of savings

Benchmark
Being “at risk” requires being able to quantify risk
Two-Sided Risk

Hospitalizations

30% admission rate 7/17-7/18

15% readmission rate 7/17-7/18
Can we risk stratify 52K patients by hospitalization?
Can we “see” 52K patients?
Can we predict their trajectories?
Can we change their trajectories?
Effectively managing a precious resource—intensive care management
Identification ➔ Stratification ➔ Care Management Interventions

See ➔ Predict ➔ Change
See
flat claims files

common data model
flat claims files

pcornet
common data model
Predict
flat claims files

common data model

Poisson Deep Factor Network

pcornet®
52K x 32 Diagnostic Categories

Month
Historical Data

- Train
- Tune
- Test

Poisson Deep Factor Network

Poisson Deep Factor Network
This “Deep Care Management” framework:

- Doesn’t do the same thing every month; it learns over time.
- It therefore has historical memory and will adjust as interventions change outcomes.
- We can integrate feedback from providers to influence its learning.
- Regardless of our current interventions, we have a population risk metric with which to assess them.
change
Betty C.

A pharmacy technician visits Betty at her home.

Helps her understand her medications.

Links her to resources for financial support.