Machine Learning Approaches to Predicting No-Shows in Medical Appointments

Problem Statement

- **Problem 1:** Dr. Dave Friesen & Associates is a San Diego based outpatient medical practice losing nearly $250,000 annually from unattended medical appointments.
- **Problem 2:** Appointment no-shows or cancellations typically result in decreased practice efficiency, lost time, lower patient satisfaction, and added stress on staff. For a doctor working an eight-hour shift full of 20-minute reserved appointments, three unfilled cancellations cause a productivity decline of 12.5%.
- **Problem 3:** On a monthly basis, we average 86 established patients who do not show and 43 new patients who do the same.

Financial Impact

Staff

Impact

- Accurate Schedule
- Dedicated Time
- Better service
- More Productivity

Clinic

Impact

- Accurate KPI’s
- Better time usage
- C.S.S Improvement
- Service Quality

Enterprise

Impact

- Exceed regulations
- Predict NS Rate
- Visualize Trends

  within that NS rate

Our end goal is to have the model be a baseline, be able to identify Key areas on why people cancel, so we can determine the best action plan to retain potential capital, and increase overall revenue.

Solution: Machine Learning Prediction

Using a machine learning algorithm we can take structured data provided by our EHR, create features that can extract more knowledge for our Machine learning model. Implementing a machine learning Model into our business can help use reduce various issues when It comes to no-show clients. The benefits to adding in a machine learning algorithm can include, more productive staff, bottom line prediction, improved labor to productivity benefits, and much more.

Other Solutions Considered

Follow up Staff

This is a risky thing to do by hiring staff that only call clients to remind them they have appointments and if they need to reschedule

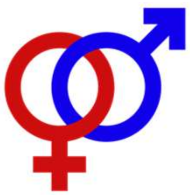
Cancelation Charges

This could have adverse effects on losing clients due to having extra charges due to them missing their appointments

Allowing double booking

This is a very complex thing to do, as we have to structure staffs schedules to allow to pick up other staffs appointments

Feature Selection



Gender

Gender could play a role for who is more likely to show or not for appointments

Call date To appt date

Looking at the distance from peoples call date to their appointment time, shows how committed they are to the appointment.

Neighborhood

This is the first step into seeing how far peoples addresses are from the location . which if we have their address, we could calculate distance to the office

Age

Age is another key component, because adults can drive themselves, were as 16 and under have to rely on their parents to drive them

Model Evaluation

Gradient Boost

Gradient Boost

Works extremely well on categorical data, is robust for generalization, with many factors on why someone would no show.

Can help Identify Key Features

Gradient boost models, can create complex relationships that we can not detect with our naked eyes, and identify underlying trends

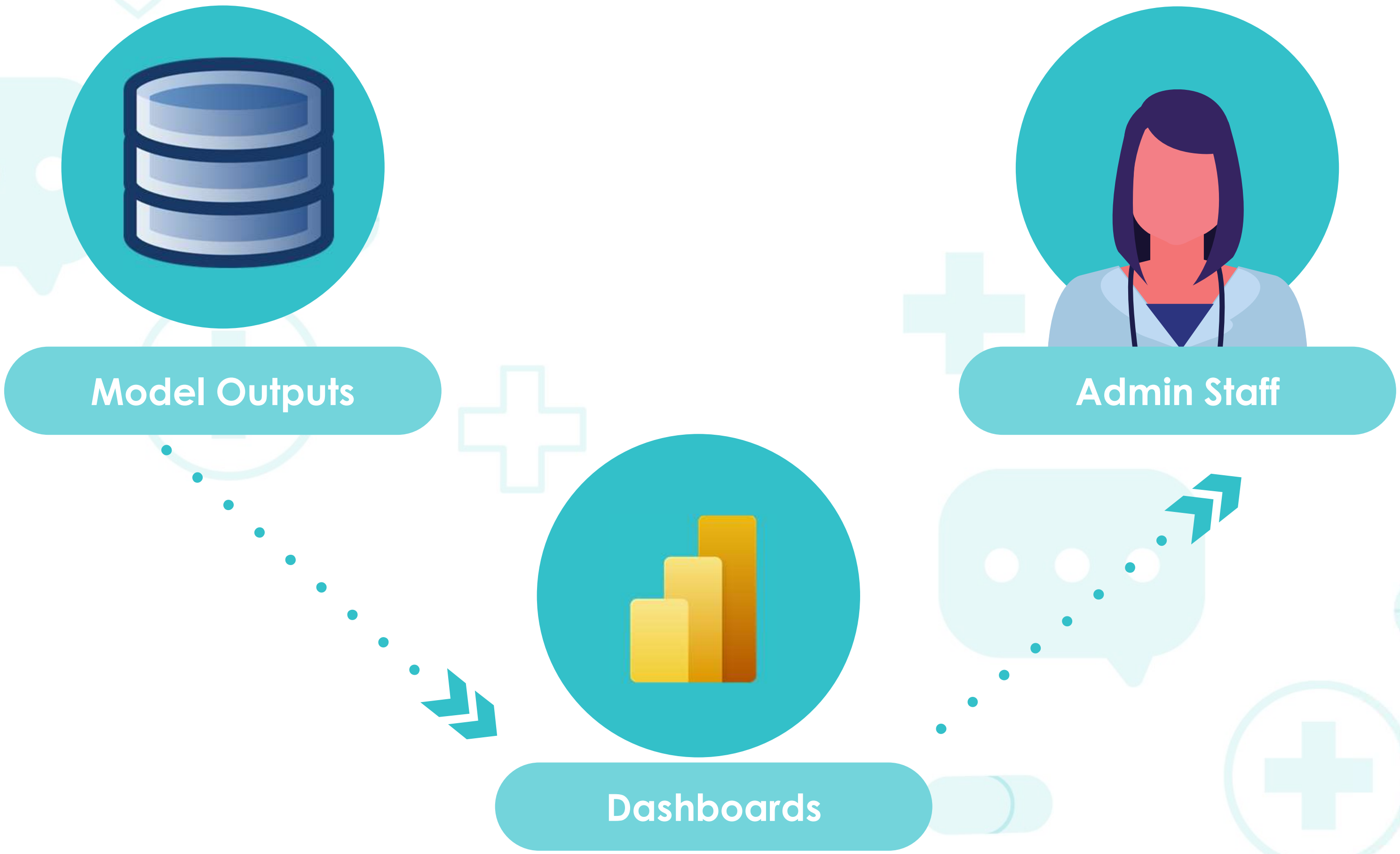
Ease of Optimization

We can fine tune the model even better after we run an initial baseline, with other categorical variables. (Grid Search)

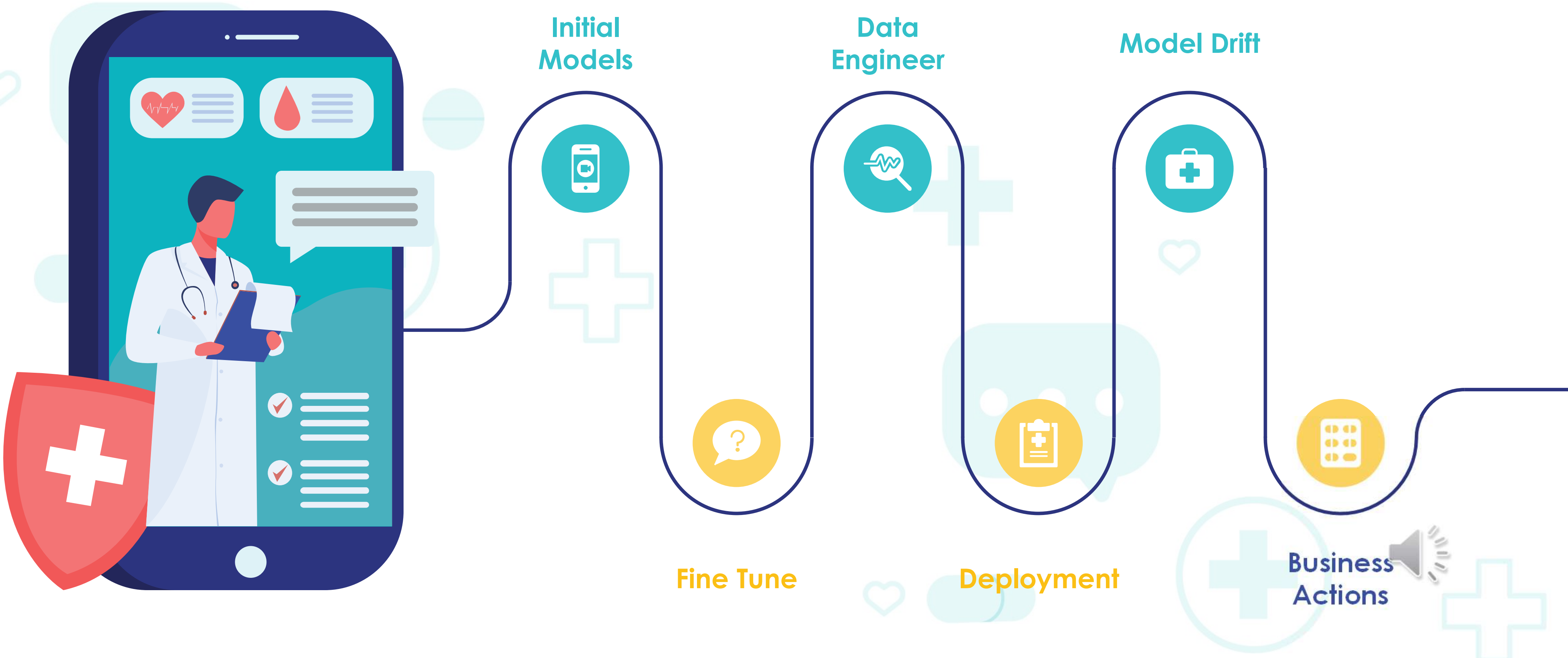
Flexible with missing Values

One key thing especially when dealing with healthcare data is missing values. Clients do not have to list anything that identifies them based off of age, race, or gender due to HIPPA.

Solution Pipeline



Model Deployment Outline



Action Steps After Deployment

Testing call Staff

Testing if we have staff call, at some point during the week to get patients to come in or “Double confirm” their appointment times

Changes in workflow

Changing staffs workflow, to allow them to accept more walk in appointments during times when people are predicted to not show.

Measure effects

We then need to have a way that we can measure the changes that we have put in place, to compare to our model which is our baseline, then see if the improvements have made positive or negative on the business.

Conclusion

Our end goal is to implement changes that are able to directly affect the company while technically invalidating our model by making what the model thinks is a no-show, actually show. The model is the baseline on figuring out what makes the no-shows, not show in the first place, and giving us an accurate prediction on what the appointment will actually do.

The second part is trying to eliminate as many no shows as possible, to retain capital, and help ensure staff are able to have as many appointments kept as possible. We also have to consider the fact that it will be impossible to have all no-show predictions be converted into shows, our goal is to minimize the count of no shows as possible.

Thank You . .