

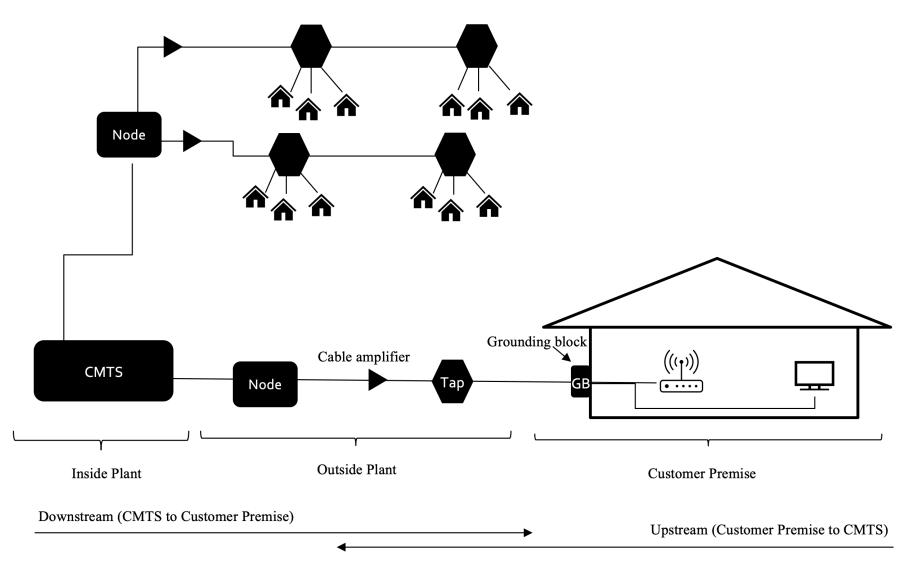






Plant is a Complex System with Many Components

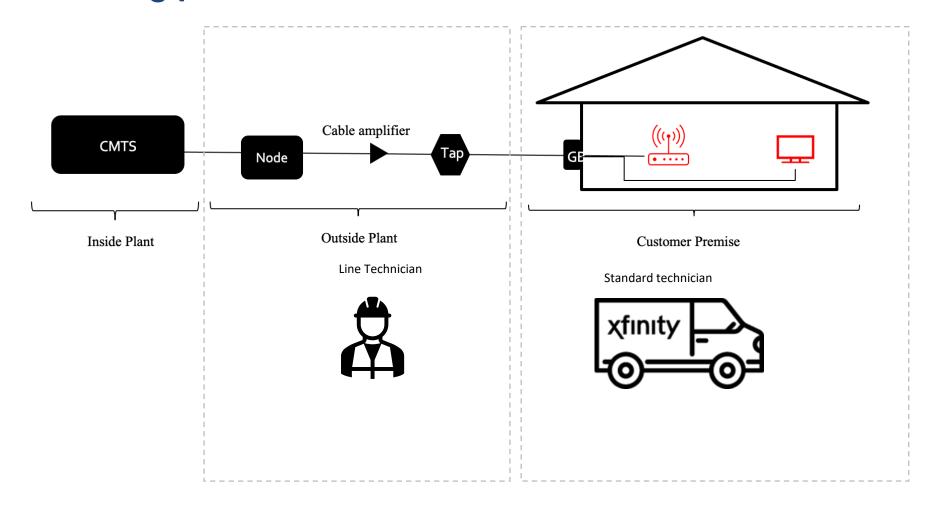




Standard and Line Technicians



Troubleshooting problems takes different skills





Right Technician at the Right Time

• 3% of technician visits end up in line tech referrals



Machine is needed Machine learning model can identify when line technician

Right Technician at the Right Time

- \$ Save cost of sending both technicians
- © Service customers better

Remote DOCSIS Telemetry Data



Node-Level Network Degradation Impairment Analysis Tool

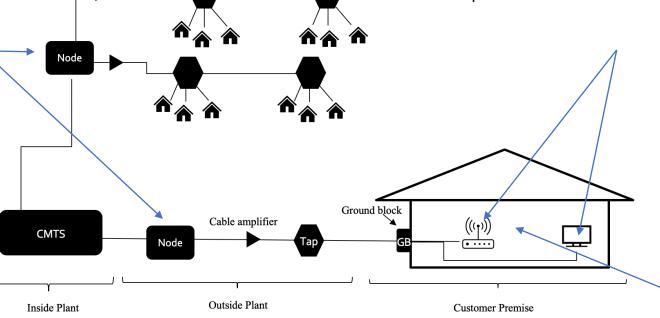
Consumes account and node-level data

 Identifies events impacting multiple accounts

 Reports outages and plant issues

Proactive Network Maintenance Software

- Polls devices several times per day
- Reports upstream, downstream telemetry such as power, SNR, FEC, ICFR, Timeouts, etc.



Account and Device Network Analysis Degradation Tool

- Consumes data from pollers and identifies impairments.
- Checks for isolated device, whole home, and neighborhood impairments

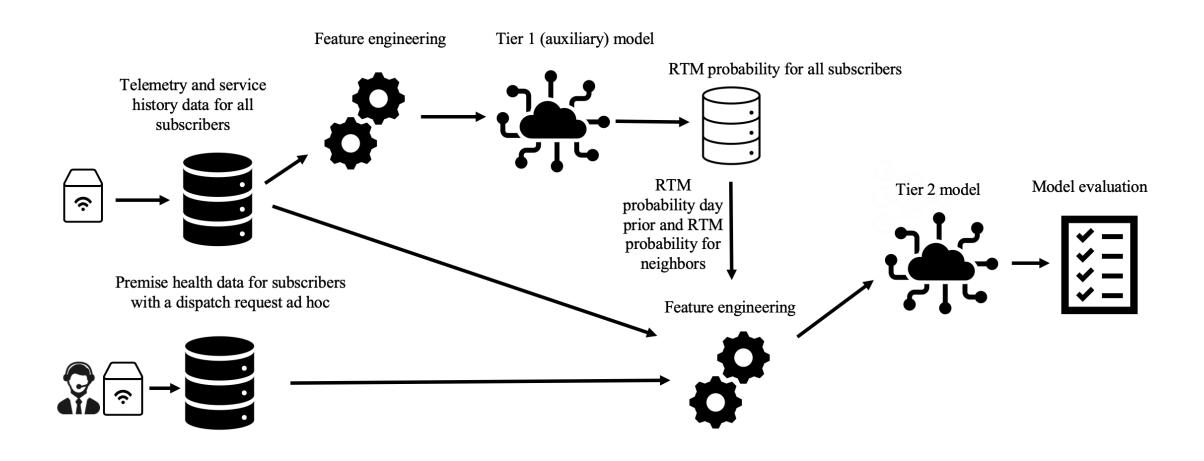
RTM Machine Learning Model



- XGBoost Classification Model
- Trained on the universe of subscribers with trucks
- Line technician visit confirmed as "valid" is target label
- Model weights to address class imbalance
- Tuned to use 500 estimators with max depth 2
- Over 400 input features
- Two-tier model approach (model stacking)

Model Training Process

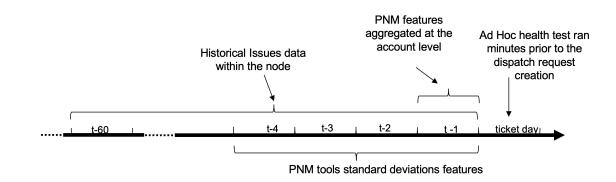




Feature Engineering



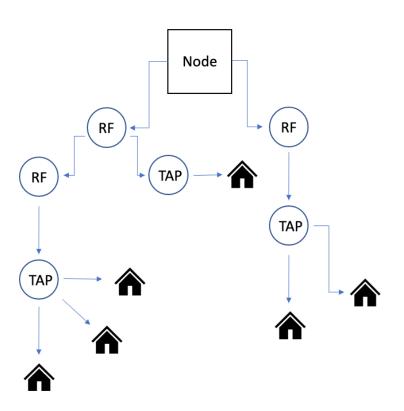
- Features from PNM poller software, device/account-level analysis tool, and node analysis tool are transformed to aggregate multiple polls to daily account-levels using min/max and avg aggregations.
- Standard deviations are examined across 4 days for selected feature
- Cumulative measures are transformed to absolute values (for counters), data are normalized (for rates calculations such as FEC)



Topology Aggregations



- Directional data representing paths from node to subscribers' homes
- Some graphs are short, others are deep
- Feature aggregations:
 - tap (parent) level
 - across amplifiers supporting the customer
 - comparisons between neighbors

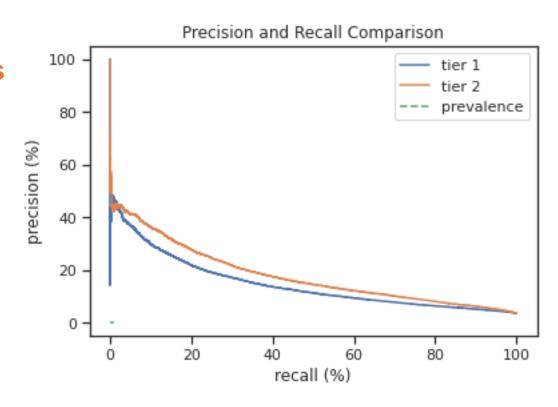




Model evaluation

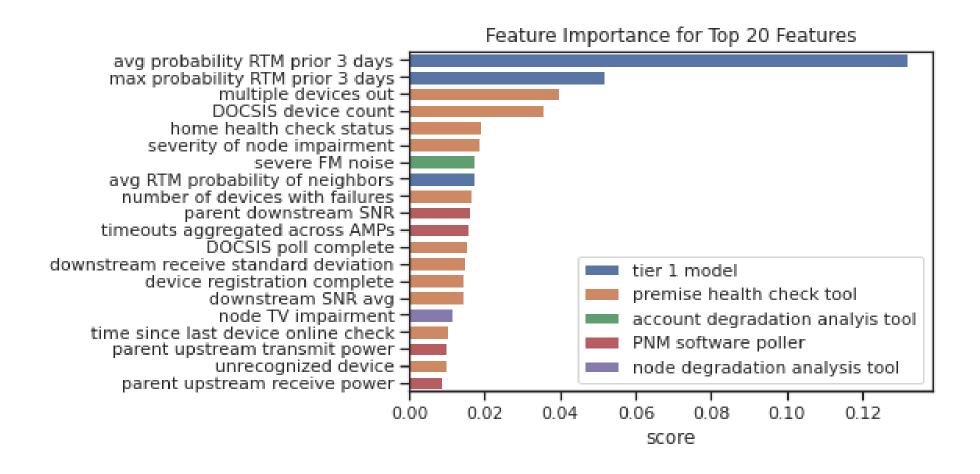
Model performs 13x better than random guess

- We evaluated the model on the outof-sample test data split on time
- At 5% recall, tier 1 model precision is 37.2% precision, tier 2 – 41%
- Tier 2 model performs 11 times better compared to the random guess (average prevalence at 3%)



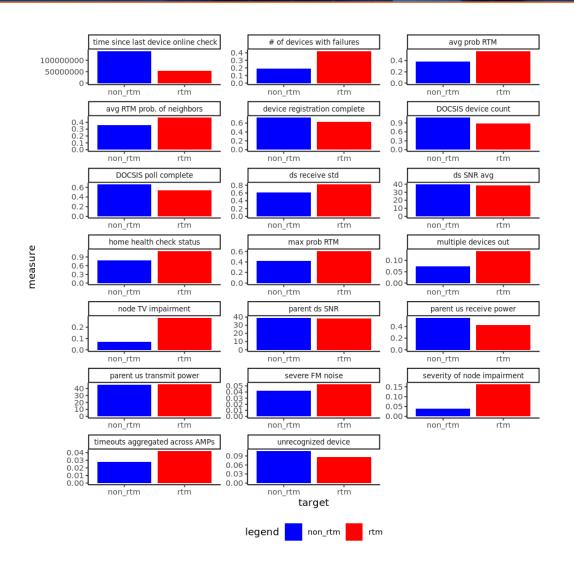
Top Importance Features





Feature Exploration





- We explore directionality of unscaled features for top 20 influential features
- Device failures, prior RTM probability, high downstream standard deviation, high number of impairments, for example, are positively correlated with RTM outcome.
- SNR, complete registrations, complete polls, are negatively correlated with RTM outcome

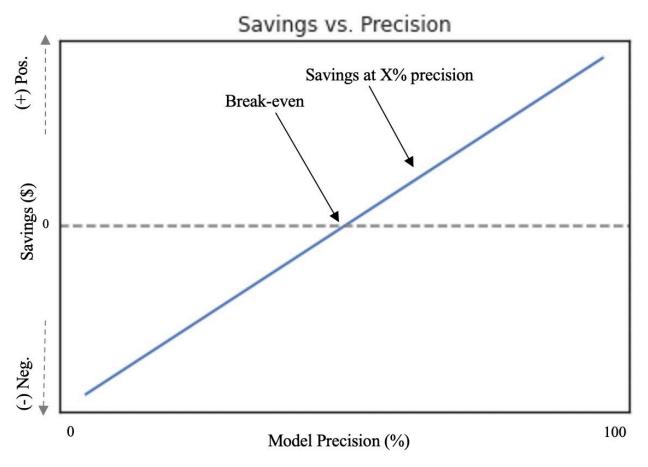


Is the Model Good Enough to Deploy?

- Cost analysis can help to define minimum precision required to incur a net zero savings relative to BAU.
- Customer-level (only customer with a truck) and neighborhood level approaches (additional the impact to the neighborhood)
- Denote
 - Cost of fulfillment truck as F and cost of line truck as L, where L > F
 - Operations and research cost as R
 - Cost of True Positive: (L+F)-F-R = F-R
 - Net Savings assuming cancelation rate Y
- Savings = $Saving_{TP}$ $Cost_{FP}$



Is the Model Good Enough to Deploy?



Net Savings:

$$((F-R)*P) - (L*(1-Y)-R)*(1-P) = S_{net}$$

$$TP \qquad FP$$

Precision to break even:

$$P_{even} = \frac{L(1-Y) - R}{F - 2R + L(1-Y)}$$

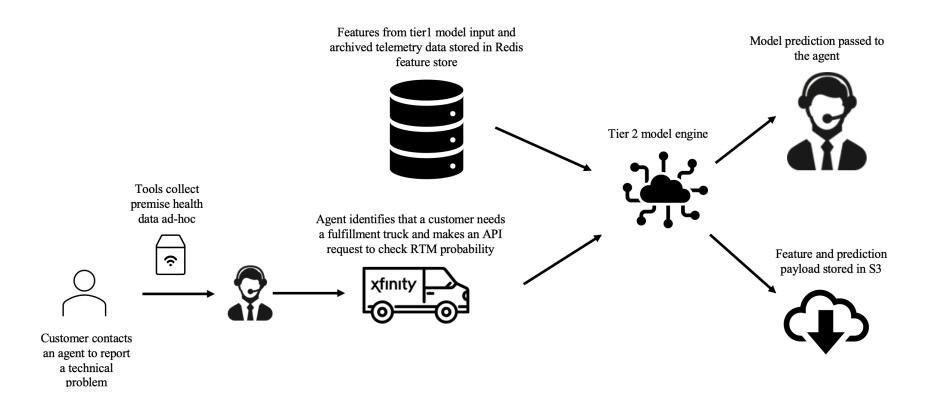
Proof of Concept Trial



"Soft" Model Deployment

- POC with a "Human in the Loop"
- We engaged 4 regions to participate in the trial
- RTM candidates sent using AWS SES and evaluated by SME off-site
- Debrief with SME helped us to discover additional data sources, improve feature engineering, and identify false positive cases





Conclusions



Machine learning is key to the operational transformation

- Telemetry measurements can help us identify impairments
- Machine learning is key to prioritizing issues
- RTM model will help us move from reactive to proactive approach
- Issues resolved in one, not two visits
- Avoiding neighborhood impact of impaired service, additional calls and trucks
- Tune the model to achieve precision to deliver net benefit to the system
- Right Technician at the Right Time



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