Using predictive modelling to help people with disability

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is a leading social purpose organisation working in more than 440 communities across Australia. We support around 18,000 people living in their own homes or in residential houses that we manage. We support:

children, young people and families
people with disability
older people
people with mental illness
homeless
refugees
asylum seekers

OUR GOAL: BETTER UNDERSTAND CLIENT NEEDS AND ENHANCE WELLBEING

exec challenge - how might we measure and improve wellbeing?

survey based metrics and KPIs - Personal Wellbeing Index (Deakin University), Net Promoter Score

internal KPIs and proxies - % clients with stable placements, % clients with health checks, dental checks, ATSI cultural connections

versus direct measures - as evidenced by client data

a candidate measure - incident frequency and severity

fewer incidents = a proxy measure for wellbeing

may include client absences, medical emergencies, medication issues, physical and sexual assault, criminal offenses, property damage, substance abuse, physical and verbal aggression, self harm, risk taking, physical or psychotropic restraint

our approach: anticipating and understanding client incidents

understand predictions to inform strategic and tactical resourcing

operationalise predictions to mitigate individual harms

BUILDING THE DATA SET: APPROACH

initial features based on sme feedback, and core system data

sme input share house composition, key worker experience and training, casualisation rates, overtime, worker fte, age at first contact, cumulative harm factors

core data client demographics, carer demographics, location, client sector, client incidents by type and severity, medical diagnoses, frequency of client carer contact, carer characteristics, frequency and type of care, progress note topics

derived features

days since last observation
running average
running sum
lag columns for key features

durations - placements, residence etc

what should our dataset look like?

some factors:

Granularity
Dependent variable
Nothing happening
Capturing the past
Sparse data
Class Imbalance
Feature selection

our target data transformations

timestamped event per row, including client-day ‘reference’ rows, then

PIVOT to consolidated client-day per row, then

GROUP to consolidated client-month per row, including dependent variable

BUILDING THE DATA SET: IMPLEMENTATION

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our etl-bi-analytics stack

Open for Innovation®
KNIME

aws

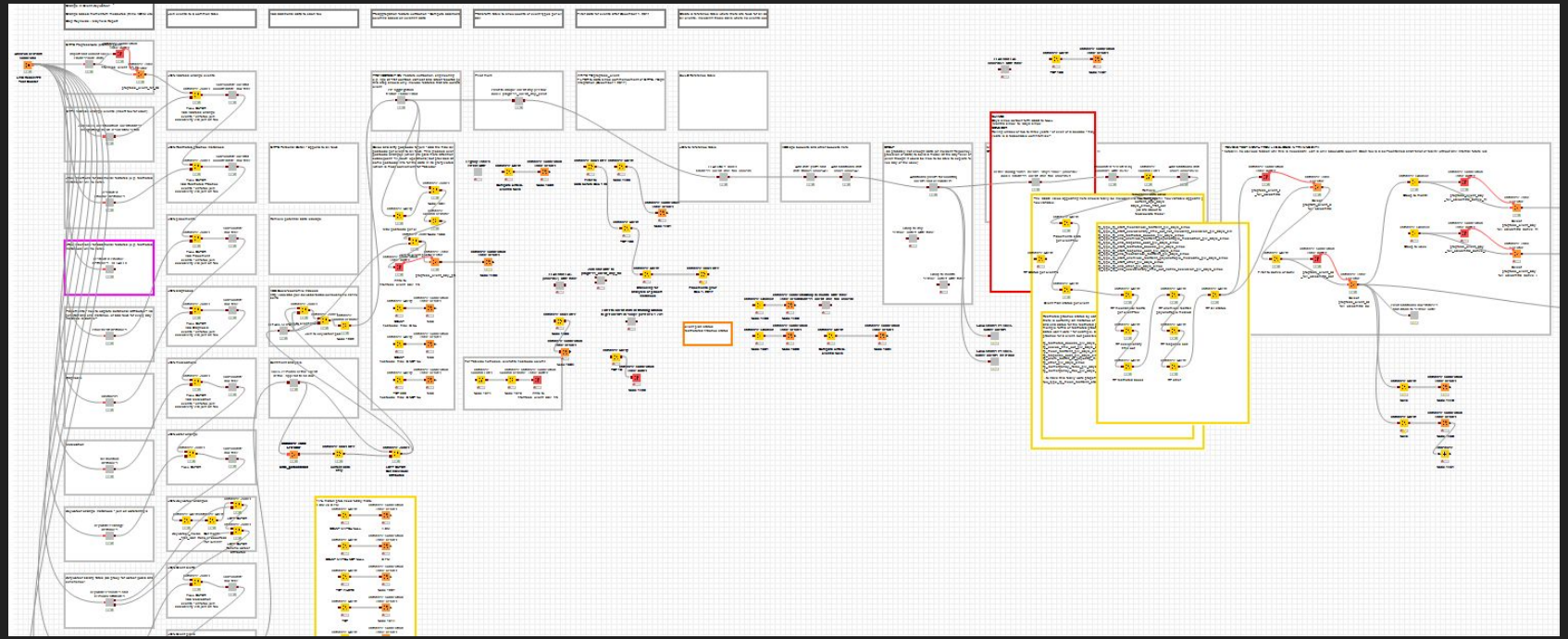
tableau

Forest Grove Technology
Better Information | Better Decisions | Better Outcomes

feature derivation using knime and aws redshift

use knime loops to build large sql statements (sum, avg, lag) to run on redshift

knime data pipeline



resultant training data

ClientID	New Client ID?	Year-Week	DOB	State	Incident Instances > 0	Weeks since last critical incident	Significant Incidents Moving Average	Week Positive Progress Note Instances	Week Negative Progress Note Instances	Weeks since last placement change	Has diagnosis type A
C0001	1	201601	20000127	VIC	0	99	1	2	0	99	1
C0001	0	201602	20000127	VIC	0	100	1	1	1	100	1
C0002	1	201601	19881111	QLD	1	0	0	1	3	99	0
C0002	0	201602	19881111	QLD	0	1	0	1	0	0	0

MODELLING

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We all share the responsibility for child safety

temporal order preservation for training, validation and testing

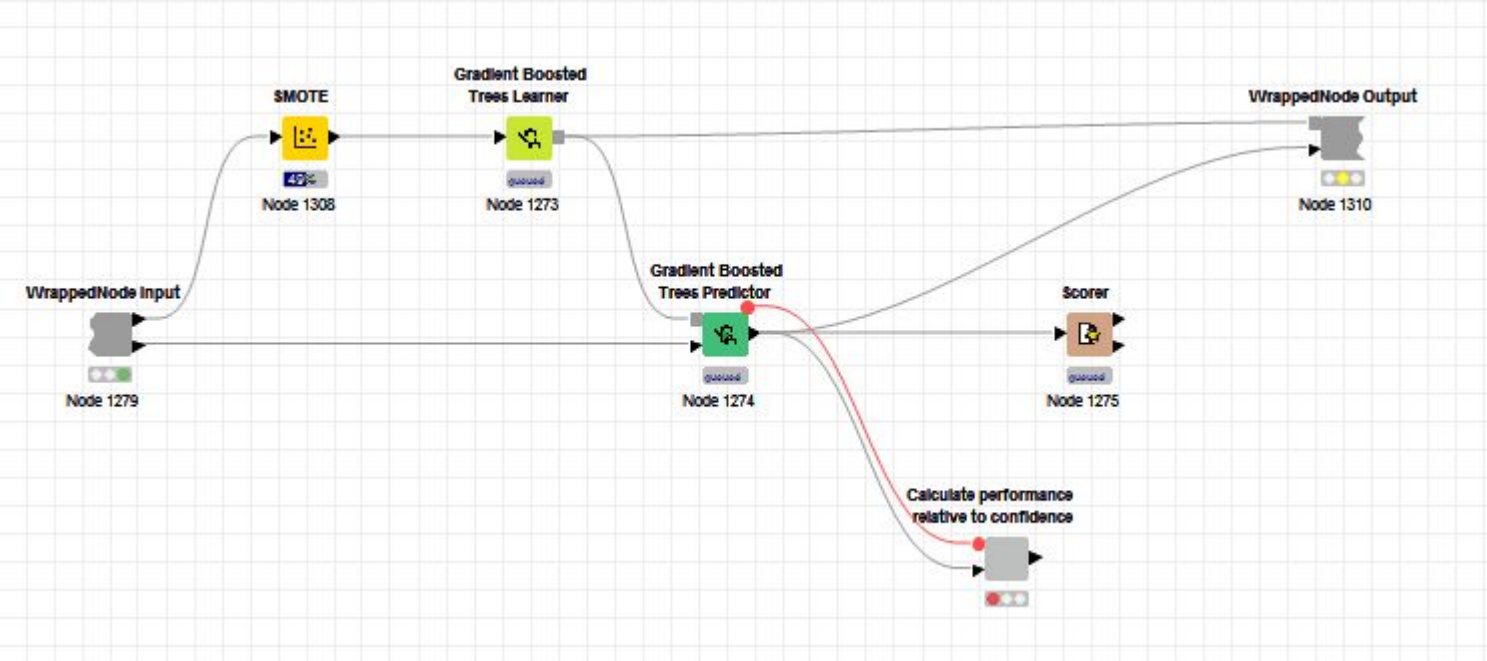
training set A - most recent month-3 and earlier

validation - most recent month-2

training set B - most recent month-2 and earlier

test - most recent month-1

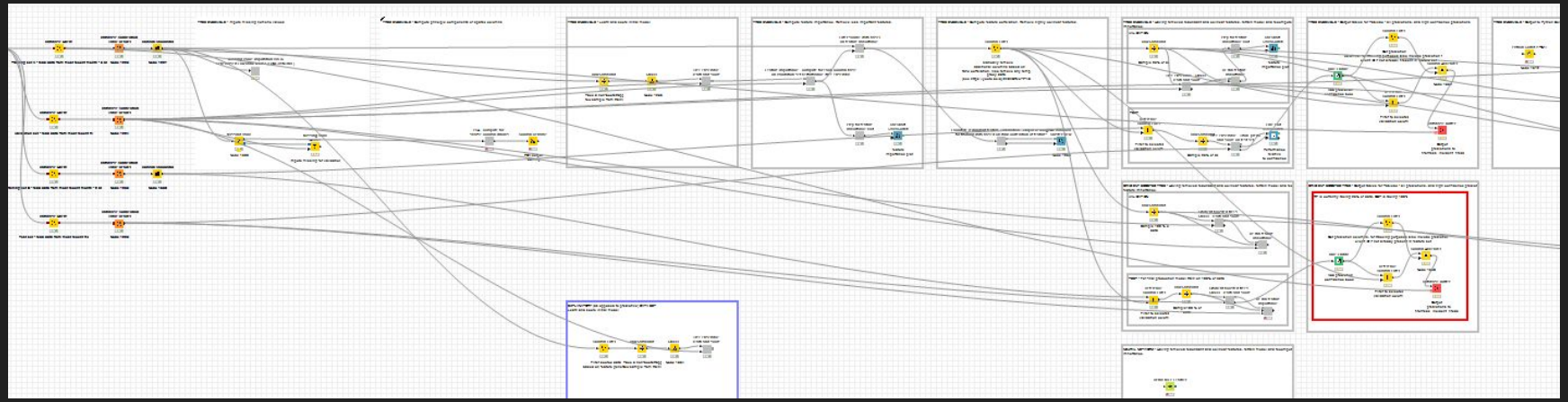
smote, random forest / gbt



knime ‘graphical notebook’

horizontal - steps incl data prep, initial training, pruning, re-training, validation

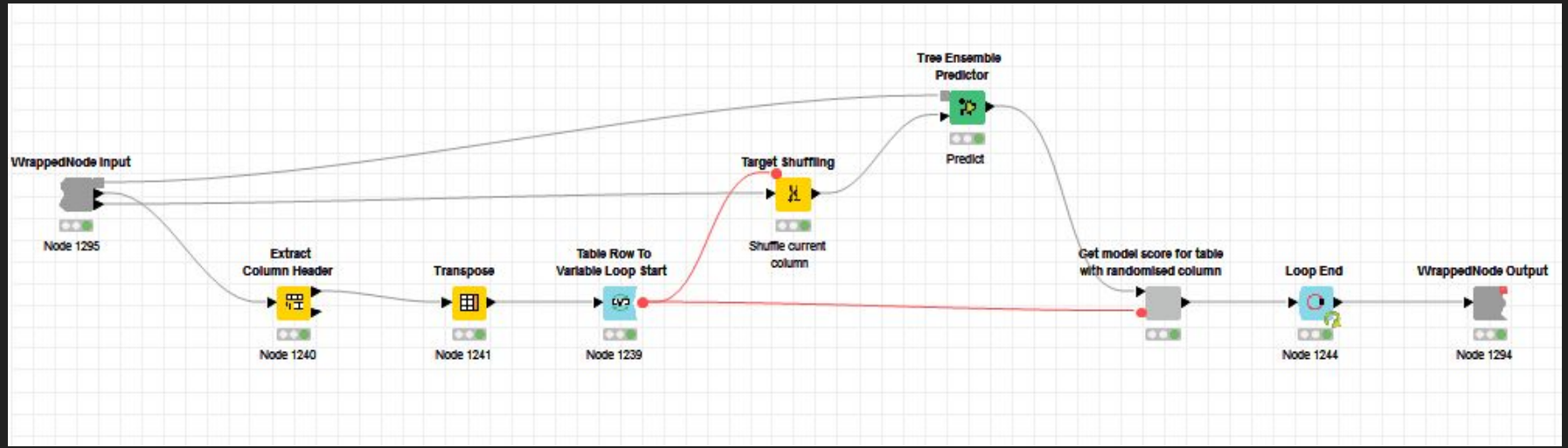
vertical - different models (tree ensemble, gbt) and sample sizes



TUNING AND INTERPRETATION

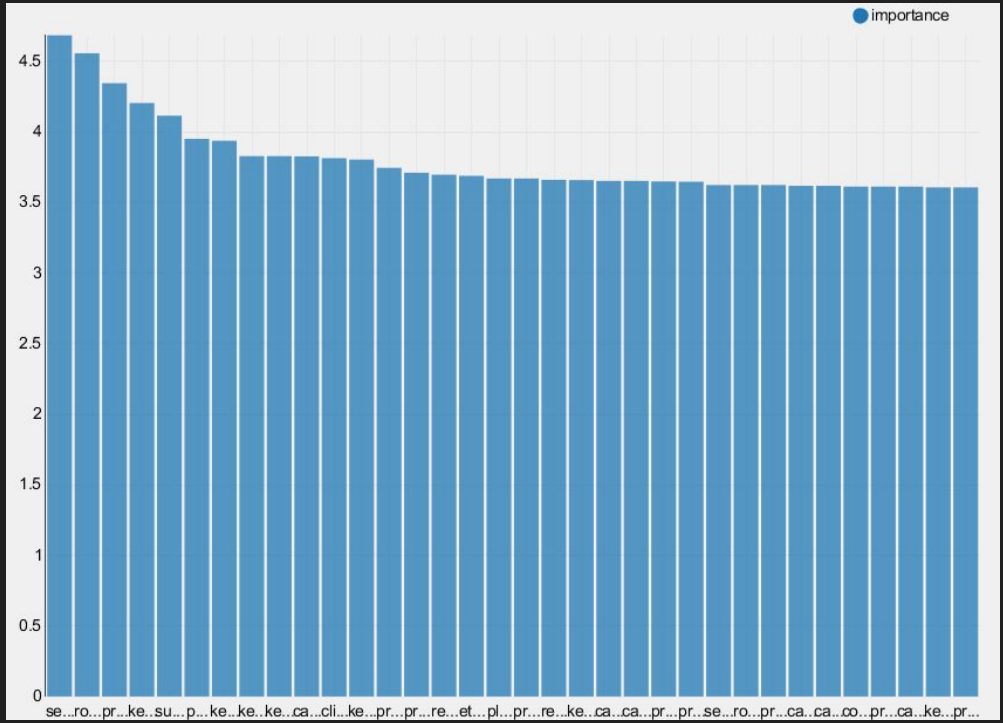
feature importance, pruning

feature importance via column value shuffling

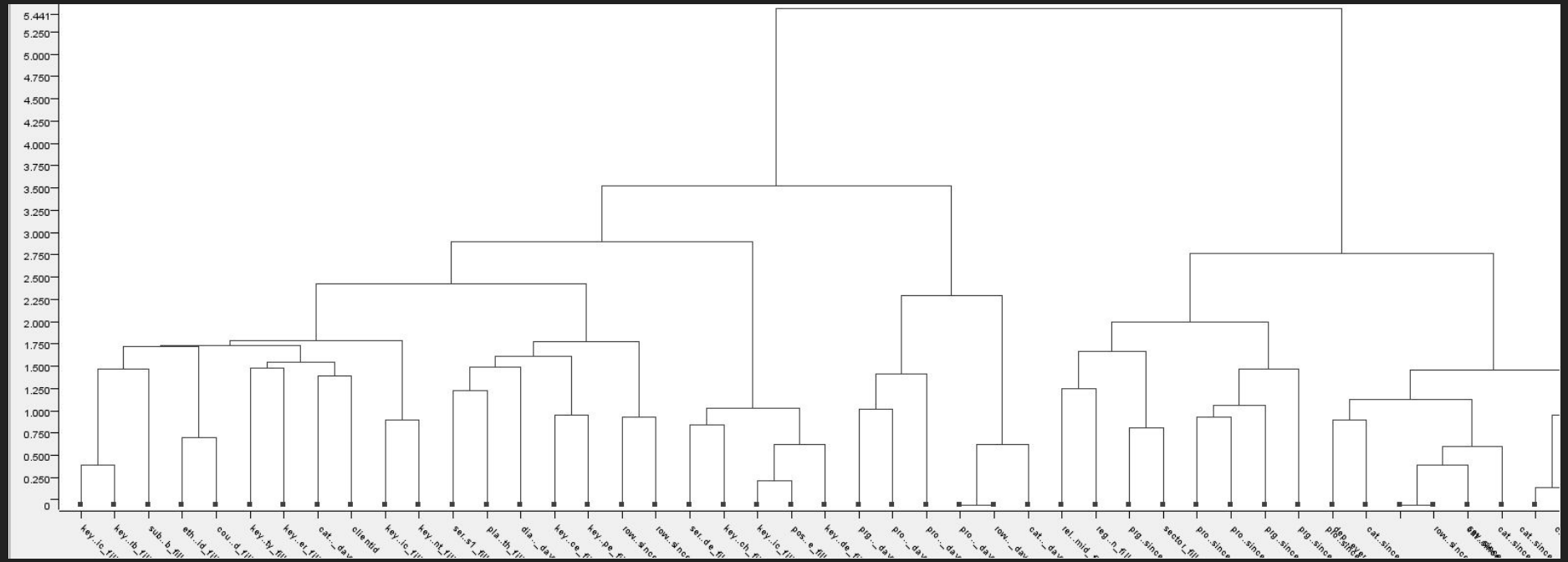


feature importance plot

importance determined by 1/f-measure when scrambled

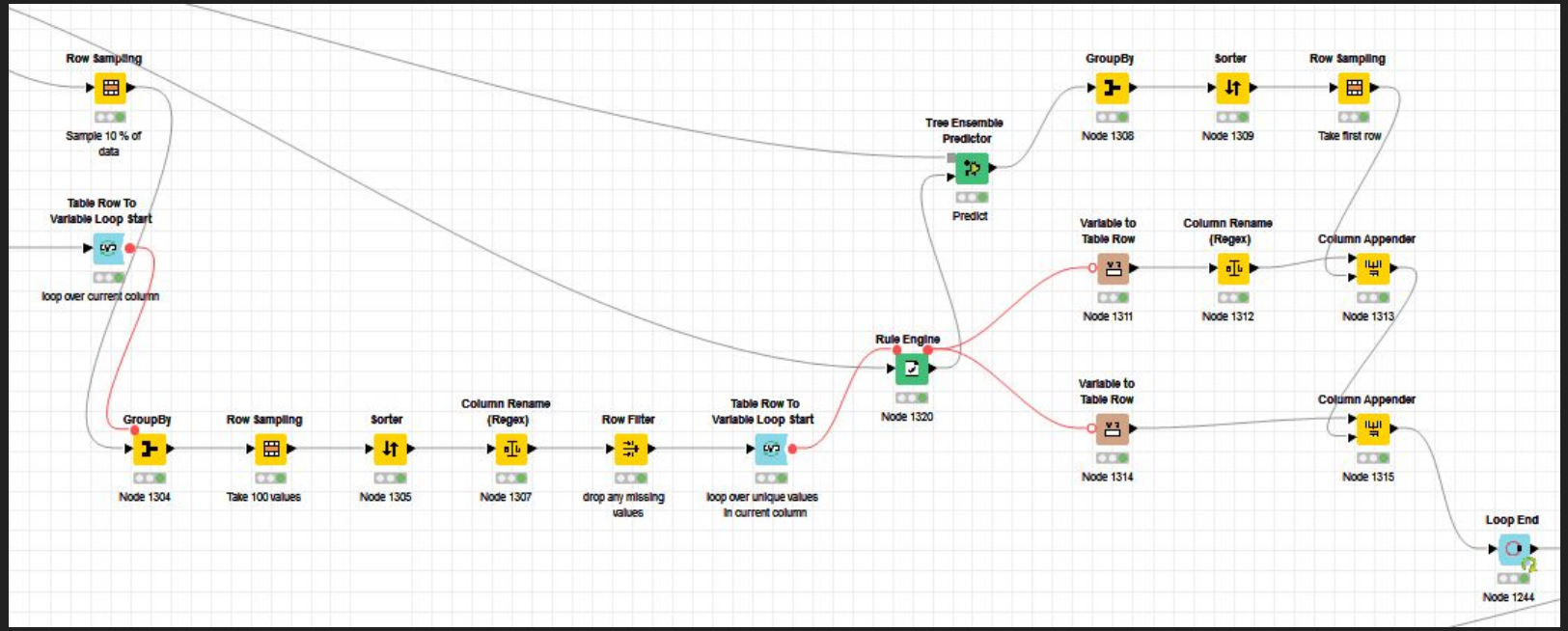


prune (rank) correlated features



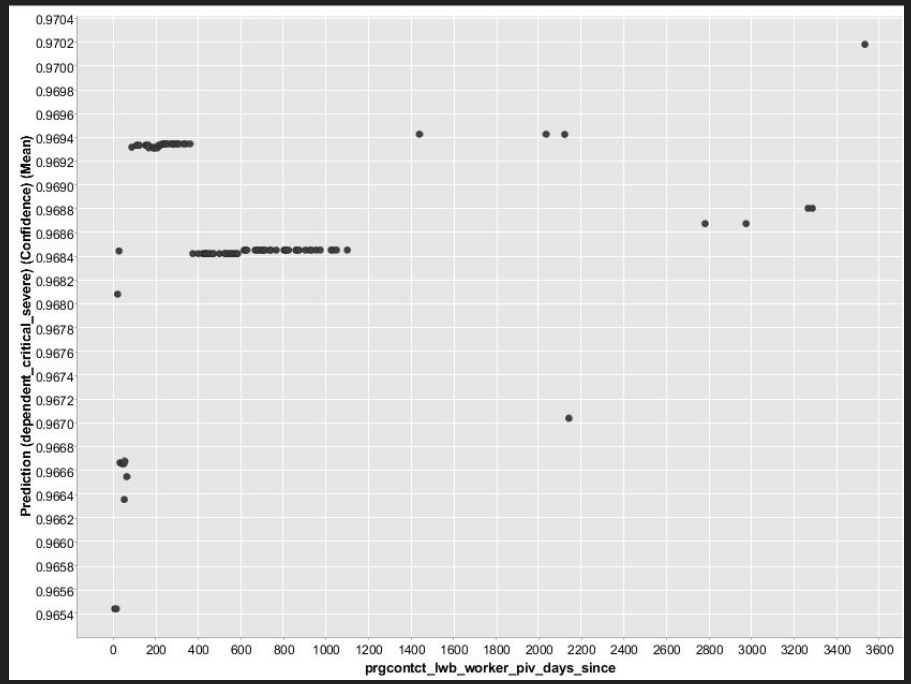
interpretation: partial dependency

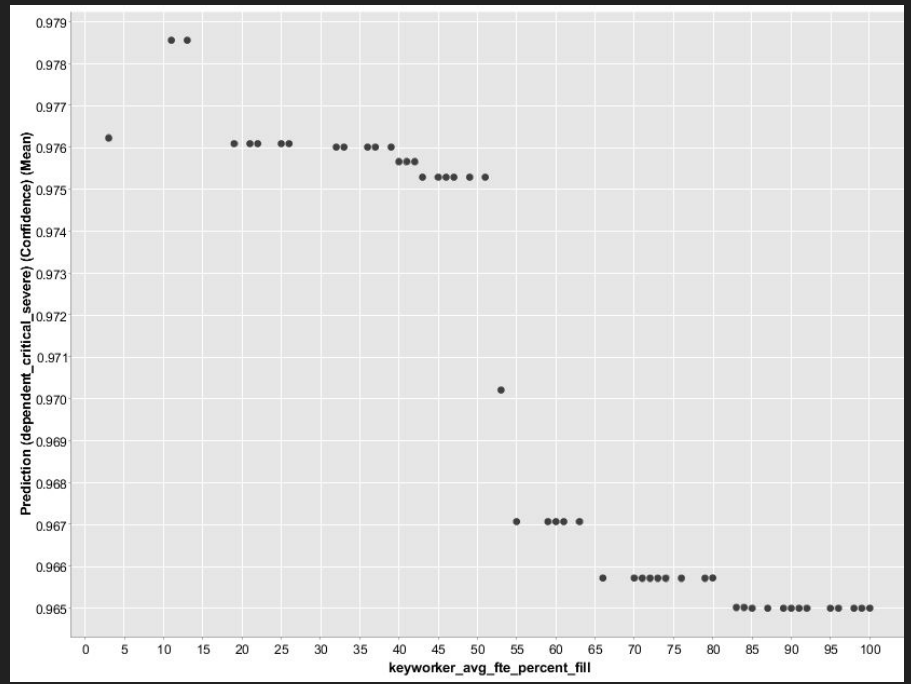
measure prediction output while for a given feature, fixing every row to the value being tested, and then so on for subsequent test values



partial dependency

non-event tree ensemble *prediction confidence* varying based on specific feature values - days since keyworker contact (left), keyworker fte (right)





RESULTS TO DATE

model performance

~ one third accuracy in predicting severe and critical incidents in a coming month based on recent CIRTS data patterns (GBT)

Row ID	D Recall	D Precision	D Sensitivity	D Specifity	D F-meas...
non-event	0.983	0.98	0.983	0.37	0.982
event	0.37	0.414	0.37	0.983	0.391

need to determine best bias/variance, precision/recall tradeoff

current aspiration, moving toward a deployment trial, is to obtain 50% prediction accuracy (50% true positives for high confidence RF predictions)

key drivers

based on feature importance and partial dependency characteristics

Lower keyworder FTE is associated with reduced risk

Recent history of multiple severe incidents is associated with increased risk

Recent contact between a client and keyworker is associated with reduced risk, except where the contact is very recent (less than 30 days)

A higher risk where a client's most recent progress note is between 50 and 100 days in the past, and

Lack of client-keyworker contact in last 100 days associated with higher risk

Plus several factors related to a specific attribute, e.g. some regions are higher risk

ETHICAL CONSIDERATIONS

privacy, consent, bias, gdpr

bias - any bias is pro-social, aimed at helping clients, however remains important to ensure that model-driven resourcing decisions are valid and consistent

gdpr - explicit client consent for data use not required in all contexts by australian law, however this may be an area where LWB can provide leadership

privacy - privacy of client data safeguarded via information security and data governance measures, also modelling approaches strip much PID

FUTURE DEVELOPMENT AND DEPLOYMENT

data set development

text and sequence analytics

missing value interpolation

cumulative harm metrics

other modeling - pca, feature clustering, deep learning approaches, hyperparameter automation

enhanced model fidelity - temporal granularity and incident severity

additional data - additional features, client feedback, wearables, IoT sensors

investigate analogous work - e.g. in education, medicine, law

model deployment, organisational strategy

trial field deployment via tableau dashboard, ‘tree explainer’ per client, intervention modelling (approaches may include design thinking, ethnography)

additional products - carer, accommodation recommender systems

potential policy & strategic responses - changed mandatory contact requirements, risk mitigation for high eft workers, increased resourcing for higher risk regions

QUESTIONS

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