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INTRODUCTION

320k

are homeless
in England

4788

are rough
sleepers

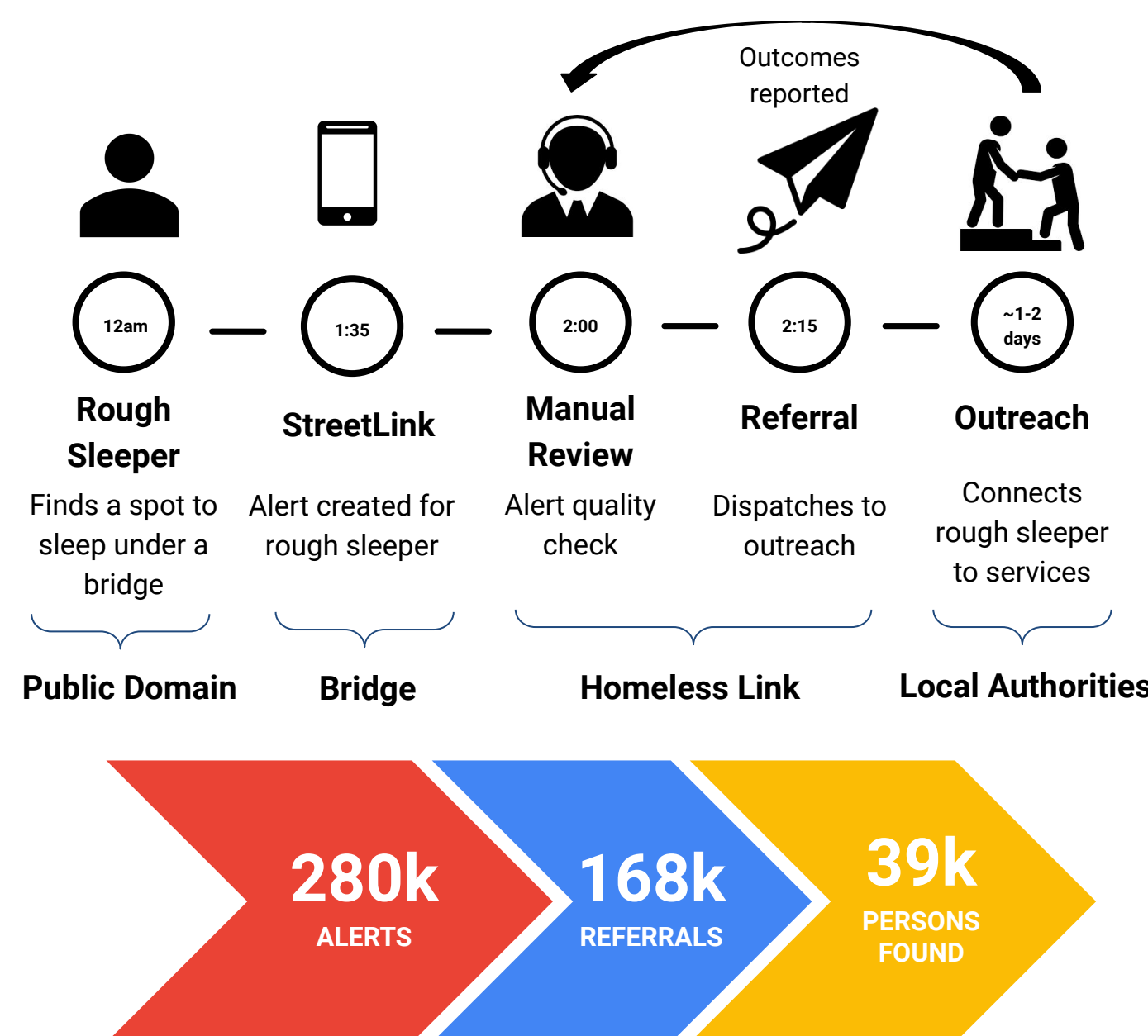
14%

of alerts lead
to finding a
rough sleeper

Homelessness is a serious and growing issue in the UK. **Rough sleepers** are those who have no choice but to sleep on the street, leaving them amongst the most vulnerable of the homeless population. Homeless Link, a UK charity, works to help rough sleepers through StreetLink, a referral platform that connects them to essential services.

METHODOLOGY

CURRENT PROCESS



GOALS

We use our models to **generate a prioritised list** of incoming alerts based on their predictions to allow StreetLink to dispatch high quality referrals more quickly.



Faster referral dispatch will **connect more rough sleepers** to services in conjunction with rapid response teams.



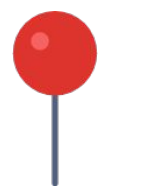
Our exploratory analysis and models help to **quantify the rough sleeper issue** to encourage positive policy change in the future.

+ data

We use internal StreetLink alert data from 2017 to 2019.



DEMOGRAPHICS



LOCATION



LOCAL AUTHORITY

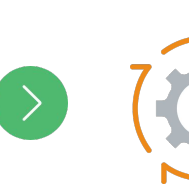
FREE TEXT
FIELDS

TEMPORAL



WEATHER

+ extract-load-transform

EXTRACT
STREETLINK
ALERT DATALOAD
INTO DATABASETRANSFORM &
CLEAN

+ feature engineering



LOCAL AUTHORITY CAPACITY:
How often did a local authority find a person last week?



SPATIAL + TEMPORAL
How many alerts have occurred in the past week at a given location?



TEXTUAL
What was the rough sleeper wearing? Where is the rough sleeper located?

+ pipeline & experiments

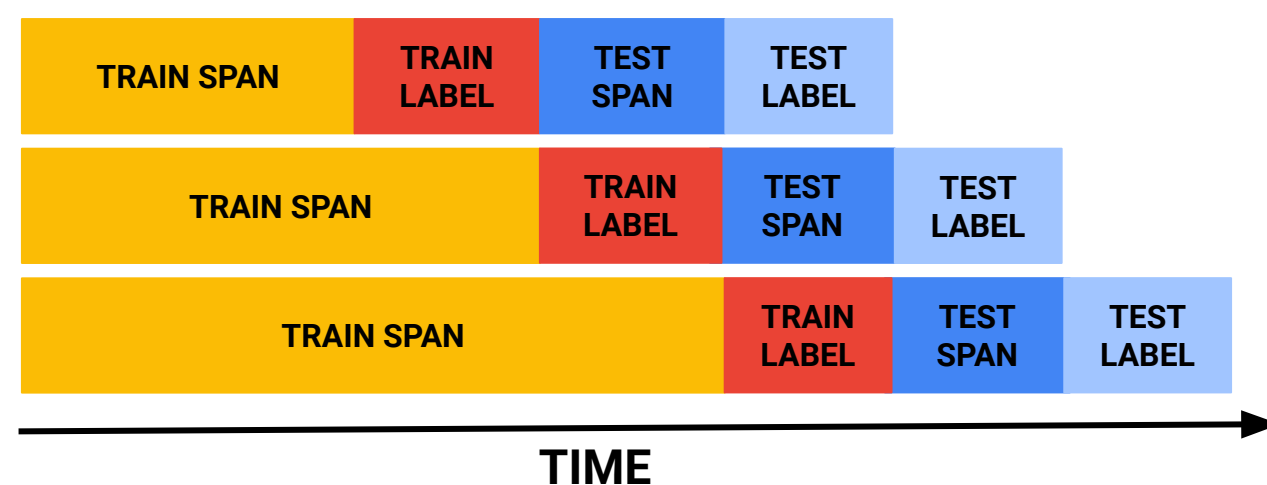


We built a machine learning pipeline to run experiments with various classification algorithms such as **Random Forest, Gradient Boosting, KNN, and Decision Trees**, with different combinations of hyperparameters and feature sets.

Each model returns an output a score for each alert indicating alert quality.

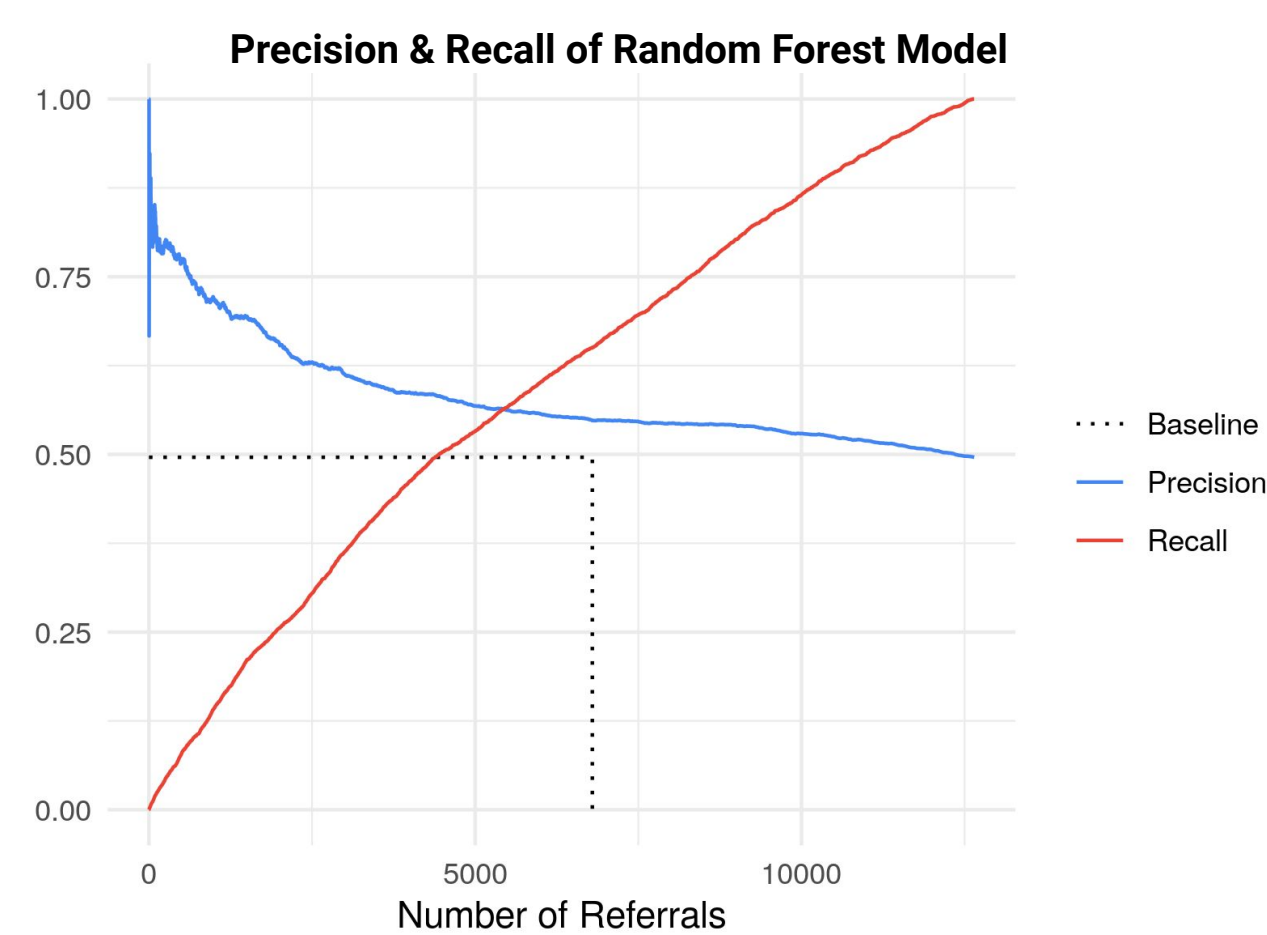
+ validation

Temporal cross-validation allows us to test and validate model performance over time.

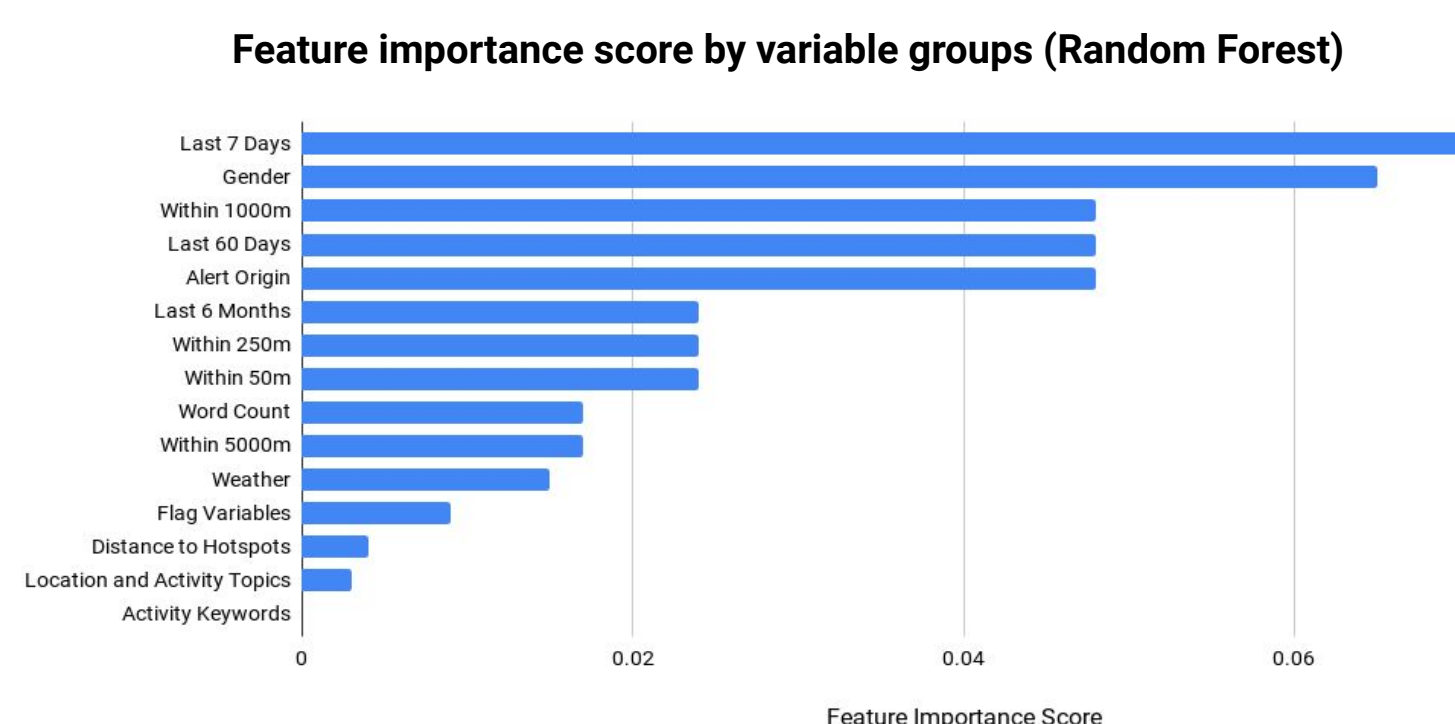


+ model selection

We selected a Random Forest model that maximizes precision at k and recall at k , where k is defined by StreetLink's resource constraints. We selected $k = 4000$.

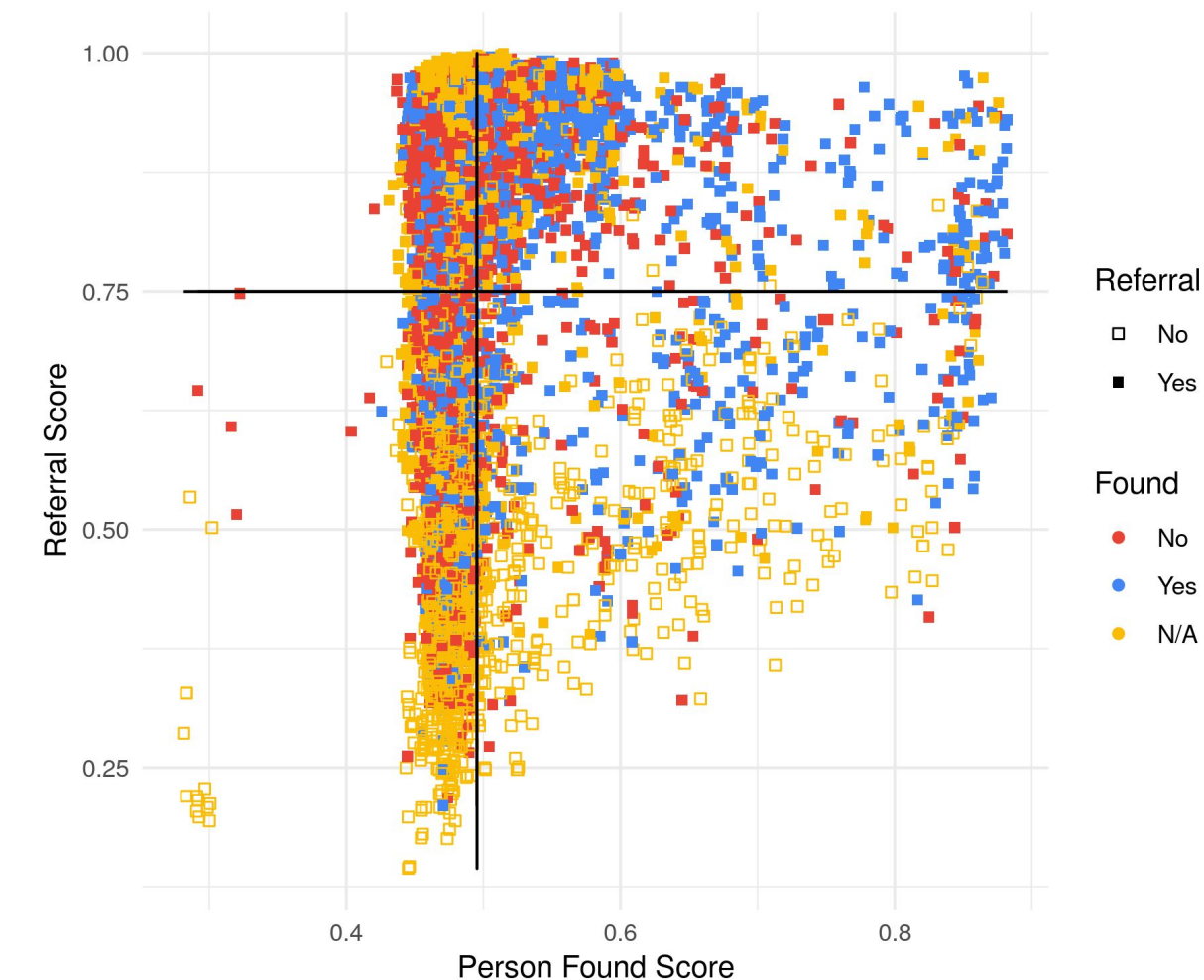


+ feature importance



This shows the highest feature importance score in each feature group from the random forest model. From 264 features, we grouped the features. **Recent temporal data** and **demographic** features were shown to be the most important in determining the likelihood a person would be found.

+ model interpretation



Our model prioritises high quality alerts and **challenges any existing biases** in StreetLink's current process.

Compared to low scoring alerts, the highest scoring alerts chosen by our model are:

- 23%** farther away from hotspots on average
- 35%** more cases of time seen
- 85%** fewer alerts by phone

★ results

{ **18%** }

INCREASE IN ROUGH
SLEEPER FOUND RATE
WITH OUR MODEL

IMPACT



Better connect rough sleepers to services



Reduce time a person is forced to sleep rough on the streets



Advocate for policy changes to help rough sleepers

Thank you to our partners at Homeless Link and the StreetLink Staff for sharing their time, data and knowledge with us.