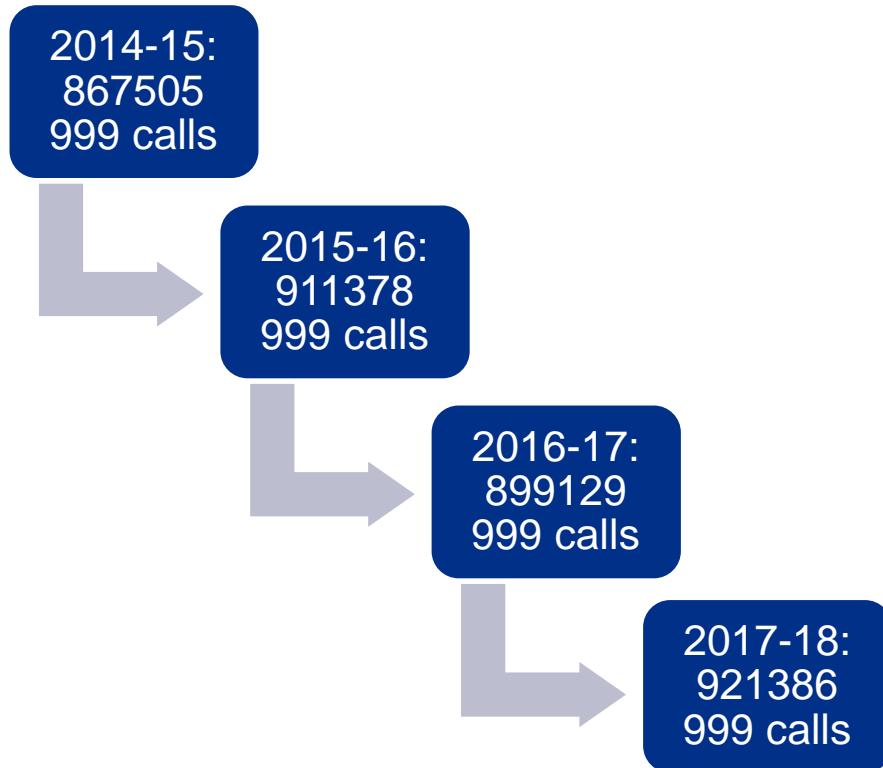


Can dispatch codes be used to determine when an ambulance is *really* needed?

Jessica Lynde,
South Western
Ambulance Service

Background: Current pressures



National Standard	Target
Category 1 Mean Response Time	7 minutes
Category 1 90th Centile Response Time	15 minutes
Category 2 Mean Response Time	18 minutes
Category 2 90th Centile Response Time	40 minutes
Category 3 90th Centile Response Time	2 hours
Category 4 90th Centile Response Time	3 hours

Winter Pressures period:

Daily call volumes rise from avg. 2524/day, to avg. 2791/day in December 2017, (peak of 3521 calls on 30 Dec 2017).

DCR table (select examples)

Dispatch code	Description	Response category
01C02	Known Aortic Aneurysm	CAT2
01D01	Abdominal Pain and Not Alert	CAT2
02C01	Allergic reaction with difficulty in breathing or swallowing	CAT1
06D02A	Difficulty speaking between breaths - known Asthmatic	CAT2
06E01A	Known Asthmatic with Ineffective Breathing	CAT1
07O01	Minor burn less than hand size	CAT5
09E02	Cardiac / Respiratory Arrest - Breathing Uncertain	CAT1
12A01E	Not fitting now Breathing Effectively - Known fitting disorder	CAT3
15D02L	Unconscious post Lightning Strike	CAT1
17A01	Fallen with non-dangerous injuries with deformity of limb	CAT3
17D04	Not Alert after Falling	CAT2
18A01	Headache normal breathing and no priority symptoms	CAT5
21D04T	Dangerous Haemorrhage Trauma Bleed	CAT1
22D01	Mechanical or Machinery Entrapment	CAT2
26O26	Sore Throat (No Difficulty Breathing/Swallowing)	CAT5

Risk scoring methodology

Call Outcome Risk Score

(i.e. % attended and % conveyed) +

Emergency Conditions Risk Scores

(% Cardiac Arrest or STEMI or Stroke) +

Clinical Intervention Risk Score (e.g. airway device or abnormal ECG rhythm detected) +

Medication Risk Score

(drugs administered)

⇒ **Final Composite Risk Score**

for each dispatch code

Risk stratification table (simplified example)

Dispatch code	Call Outcome	Emergency conditions	Clinical Intervention	Medications	Composite Risk Score
13A05	0	0	0	0	0
26A01	1	0	2	0	3
02B02	3	0	2	3	8
31B04	5	3	5	5	18
04C03	7	4	6	7	24
17D02	9	7	7	6	29
09E01	8	13	6	5	32

Risk stratification model – sliding scale

Dispatch code	Call Outcome	Emergency conditions	Clinical Intervention	Medications	Composite Risk Score
13A05	0	0	0	0	0
26A01	1	0	2	0	3
02B02	3	0	2	3	8
31B04	5	3	5	5	18
04C03	7	4	6	7	24
17D02	9	7	7	6	29
09E01	8	13	6	5	32

The Project: aims, methods, PPI

Aim: to rank dispatch codes by typical clinical acuity of the patients in those codes.

Method: Machine Learning to locate algorithm to rank codes by 'relative need for an ambulance'.

Using Python programming language on Anaconda platform.

PPI group: ML in ambulance service – importance of patient medical history and co-morbidities. Operationalised as 'patient reattendance'.

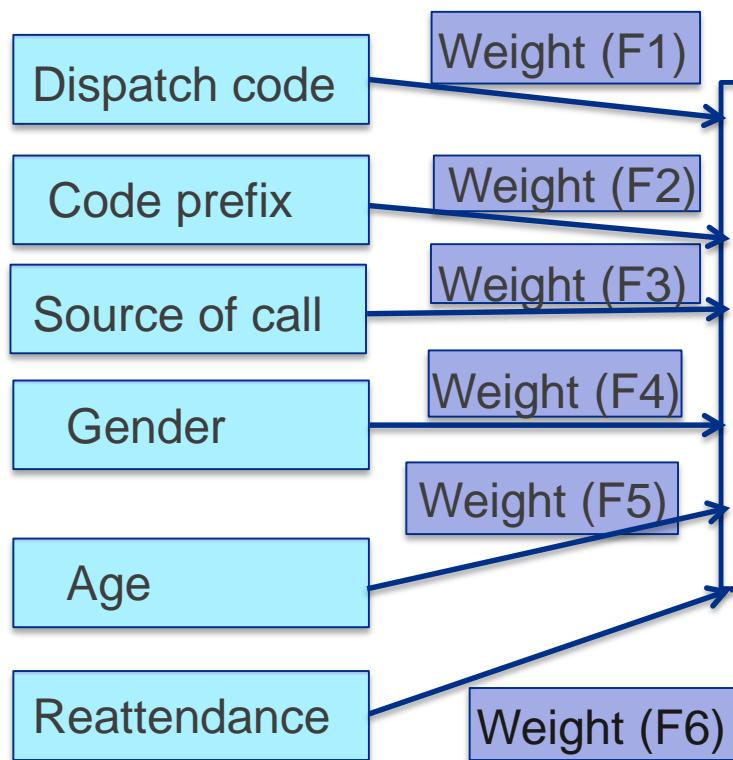
Phase 1 model

Use call-taker info (dispatch code and other items) plotted against conveyance.

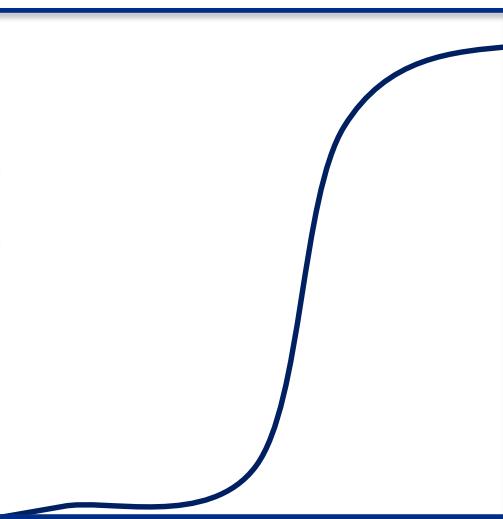
Built and ran a series of Logistic Regression models to test out optimal sample sizes and model regularisation, to boost accuracy.

Algorithm generation for phase 2

Features (data items):



Model identifies accurate algorithm...



Probability of outcome 1 (or 2 or 3 or 4)

Outcomes:

- 1: *Neither intervention nor conveyance;*
- 2: Intervention only (need paramedic);
- 3: Conveyance only (need ambulance);
- 4: *Both intervention and conveyance.*

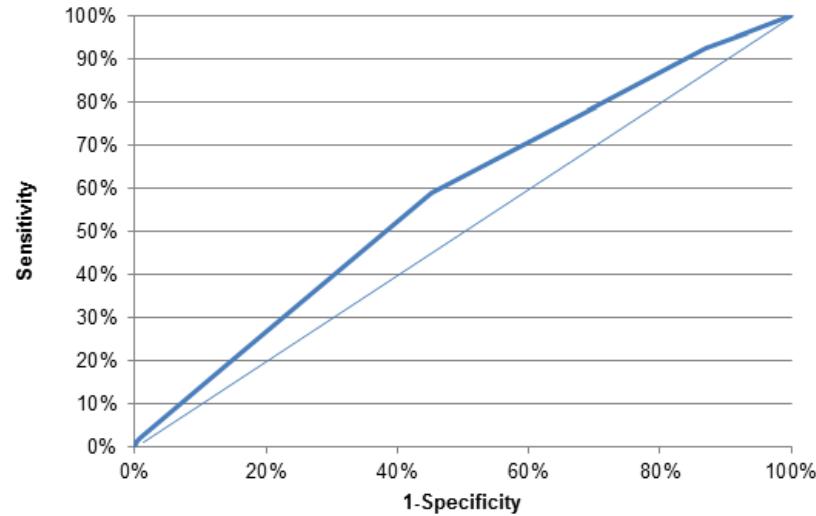
Phase 2: findings

Outcome	sample %	Log Regression		Random forests		Support Vector Machine	
		Best accuracy (%)	AUC	Best accuracy (%)	AUC	Best accuracy (%)	AUC
1	25.2	76.4	0.727	75.2	0.649	76	0.585
2	9.5	91	0.708	91.2	0.599	90.9	0.545
3	24.2	77.7	0.71	75.8	0.645	77	0.593
4	41.2	64.6	0.677	60.4	0.609	63.8	0.624

AUC = Area under the curve (measure of sensitivity and specificity)

Phase 3, and extra model

Test whether the scoring methodology in our Risk Stratification model can locate codes 'not requiring an ambulance'. Best accuracy was 75% and AUC = 0.578 (little better than random guess – see Receiver-Operator Curve, right).



Extra stage – code and call-taker info plotted against Cardiac Arrest, STEMI and Stroke. Much more successful, best accuracy was 97.5% and AUC = 0.846.

Could machine learning help us better triage certain patient condition groups?

Impacts

This project: the risk stratification model is in active use e.g. increasing HART team utilisation, and Enhanced Hear and Treat trial. HSMA project allowed for balanced pragmatic approach by senior decision makers.

Scope for machine learning in future work:

A tool to replicate the method – both offshoots of this project and other applications. Ideas from colleagues inc. modelling necessary supplies of Morphine by patient group and geography, for medicines safety.

Impacts

Scope for other OR methods:

System Dynamics – ambulance service regional coverage, so multiplicity of different local pathways – SD could identify where processes fall down.

Simulation – identify bottlenecks in ambulance job cycles.

For organisation: modelling to allow us to test out new initiatives in virtual environment before real world. Reduce risk and help to prioritise ideas. Gives Hannah and I expertise to guide organisation to test/evaluate initiatives with this new methodology, which will be spread through training colleagues and educating decision makers.