Service & Repair Demand Forecasting

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European R Users Meeting

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We supply energy and services to over 27 million customer accounts

Supported by around 12,000 engineers and technicians

Our areas of focus are Energy Supply & Services, Connected Home, Distributed Energy & Power, Energy Marketing & Trading





Overview



Gas boiler service & repair demand

- Strong causality, e.g.:
 - Cold weather \rightarrow use more gas \rightarrow high repair demand
 - Holiday \rightarrow away from home \rightarrow less repair demand
- 173 service patches in the UK
 - Each has dependent variables, e.g. weather observations.



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Linear Models



model 💻 Linear fit

model 💻 Polynomial (k=7) fit

Piecewise polynomial fit 📕 (-2.92,1.74] 📕 (1.74,6.38] 📕 (6.38,11] 💻 (11,15.7] 📕 (15.7,20.3]

Poisson Distribution

• Goodness-of-fit test for Poisson distribution

<pre>> summary(gf) Goodness-of-fit test for</pre>	• poisson distrit	oution		
	X^2	df	P(> X^2)	
Likelihood Ratio	543.702	32	2.288901e-94	

• Poisson GLM

$$y_i = \beta_0 + x_{i,1}\beta_1 + x_{i,2}\beta_2 + \dots + \epsilon_i$$

Assumption:

- $y_i \sim Poisson(\lambda)$ $\epsilon_i \sim N(0, \sigma^2)$
- Response variable y_i is contact count.



Number of Occurrences

Generalised Additive Model (GAM)

 Variables may have nonlinear relationship

e.g. warm weather → low demand, but we don't expect zero demand on extremely hot day

• GAM deals with smoothing splines (basis functions) $s(x) = \sum_{k=1}^{K} \beta_k b_k(x)$

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Family: poisson
Link function: log
```

```
Formula:
contact_priority ~ s(avg_temp)
```

```
Parametric coefficients:
```

GAM: Spline function





GLM vs GAM



More Variables



Results

- For each response variable *y* we also know the standard error
 - Establish confidence interval









Accuracy measurement

Consistent results across patches

London area:





GAM Results: Aggregated View



Accuracy measurement

• Defined as 1-MAPE (%) MAX(0, 1-ABS(Forecast – Actual)/Actual)

Average accuracy of each quarter:

	year_quarter		set	`Non-priority`	Priority
*	<pre> <fctr></fctr></pre>	<0	:hr>	<db1></db1>	<db1></db1>
1	2015.1	Training	set	90.92	92.94
2	2015.2	Training	set	86.77	92.42
3	2015.3	Training	set	90.48	89.41
4	2015.4	Training	set	87.40	89.47
5	2016.1	Training	set	87.34	92.85
6	2016.2	Training	set	87.28	90.79
7	2016.3	Training	set	90.06	87.99
8	2016.4	Training	set	89.50	89.84
9	2017.1	Test	set	90.92	92.69
10	2017.2	Test	set	88.68	89.55
11	2017.3	Test	set	87.90	86.42
12	2017.4	Test	set	91.44	90.32



^{2015.12015.22015.32015.42016.12016.22016.32016.42017.12017.22017.32017.4 2015.12015.22015.32015.42016.12016.22016.32016.42017.12017.22017.32017.4}Quarter

Potential Improvements

- Feature transformation
 - Manually hand-craft *linear* features
 - Combine and transform existing variables
 - Use linear methods
 - Easier to interpret



- GAM + Bagging
- Multilevel linear regression ("Mixed-effect model")
 - Service patches as groups
 - Single model for all patches

Potential Improvements

- Time Series Approach
 - ARMA (Auto-Regressive Moving Average) / ARIMA
 - Analyse seasonality
- Other machine learning techniques
 - Boosted trees
 - Random Forest
 - Works nicely with ordinal/categorical variables
 - Neural net (RNNs)
 - Substantially longer model training time

Less interpretable, No confidence interval

Thanks

Project Team (Names in alphabetical order) Angus Montgomery Hari Ramkumar Harriet Carmo Kerry Wilson Morgan Martin Thornalley Matthew Pearce Philip Szakowski Terry Phipps Timothy Wong Tonia Ryan



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