April 2020

Written test for the position of Data Scientist

Thank you for applying to the Data Scientist position at Vector. Your profile passed the 1st screening and we would like to invite you to participate in the written test.

The next phase of the recruitment process will involve a technical interview and a human resources interview.

Before starting with the written test, please read the following instructions carefully before starting:

- Please respond to the questions in this document and return it along with an analysis script, while including your first and last name to file/document name. You ask you to please return your response by Monday 4th May midnight to marnie.simmonds@vector.co.nz
- This written test has two parts: 1) analytical thinking and 2) technical analysis
- For the technical analysis part, you have also received 2 data files (more information in the document below)
- You are expected to do the test on your own without the assistance from another person.
- As in the position of data scientist, you are allowed and encouraged to find and learn from the best by using internet searches, but referencing this material as needed is seen as essential.
- We ask you to not ask for clarifications to the questions asked and respond based on your understanding and knowledge base. Clear and concise explanations will ensure we can follow your reasoning. Good data-driven observations and comments in your response are encouraged.
- Please do get in touch if you can't access the 2 data files

Applicant Name: Jake Cherrie

1. Analytical thinking

Please choose your preferred question among the following options and respond in words only (and possibly schematics/equations) of how you would design your analysis. Your written response should be roughly half a page only (about 250 words), but strictly less than 1 page if schematics are used.

Option 1

Vector wants to carry out a peak-time rebate trial, which consists of sending customers a notification to reduce energy usage on a day where Auckland's energy use is expected to be high. If a customer manages to reduce energy usage, they receive a payment as reward, otherwise they receive nothing. The project lead has a certain budget at their disposal to pay as rewards. The project lead is looking to you to provide a written description of a pragmatic approach to identify if customers have responded to the notification and by how much, so that they can divide up the reward payment in such a way that it incentivises a customer to continue to reduce energy use when these events are called. The project lead has smart meter data (electricity consumption (kWh) in 30-min intervals) for each customer at your disposal, but if you need additional data then please highlight that too.

Option 2

Electric vehicles are a key technology to decarbonise the energy system, but the network needs to plan to integrate this new and relatively large load. The network planning manager provides you with the latest government forecast for electric vehicles in Auckland for 2030 and wonders if that total number will be evenly spread across residential customers. The manager asks you to prepare a plan for a new spatial forecast of where EVs are more likely to be adopted in the future. You are provided with a data set of annual EV adoption by suburb and some socio-demographic information, but if you need additional data then please highlight that too.

Option 2: Development of a spatial forecast of electric vehicle (EV) adoption

Step 1: Digest the problem statement and investigate existing methodologies

- Talk to the network planning manager and make sure you lock down the requirements (do they need a full 10 year forecast?, do we care about seasonal variations?, time constraints?).
- Reach out to the team behind the government forecast to see if they have looked into spatial dependence. If they (govt body) have not looked into any spatial dependence can their methodology be leveraged, extended and validated to come up with a spatially dependent model?
- Research other methods and sources; there are papers that address almost this exact problem such as (Heymann et al., 2017) which suggests the use of diffusion theory.

Step 2: Obtain any additional data and clean the datasets

- EV price data, competing vehicle price and adoption data. I suspect EV uptake will be closely related to disposable income and price.
- Make sure that the dataset supplied has all relevant socio-demographic data in it.
- Explore and clean the data; see what useful features can be engineered.

Step 3: Explore and test algorithms and methodologies

- Split out a testing and a validation set (making sure they are chronologically ordered).
- Establish an appropriate metric to assess the model.
- Depending on time constraints and your research build and test a few quick proof of concept models: ARIMA, MCMC, recurrent neural networks and other methods identified in step 1.
- Test and compare the models on the testing set before selecting a methodology.

Step 4: Refine and improve the model

- Further feature engineering (not required for neural networks).
- Clustering the suburbs together; if data is scarce in some suburbs.
- Apply seasonal adjustments, autocorrelation.
- Hyperparameter tuning.

Step 5: Validate the model

- Validate the model (check performance on the validation set).
- Hand the model over to appropriately skilled peers for review and validation.
- present the model to stakeholders If everyone is happy, move to step 6, otherwise repeat steps 1-5.

Step 6: Implement the model

- Create adequate documentation and present this to the network planning manager; ensure the model is source-controlled and recreatable (Docker is always great).

2. Technical analysis

We will ask you to do a short piece of analysis and document and visualise your results in this document, while also returning a script with your analysis (Python / R script or Excel spreadsheet)

Residential electricity load profiles

You have been provided an historical sample of residential smart meter load data for 50 residential customers and temperature data for Auckland for the full year 2015. Smart meters measure electricity consumption (kWh) in 30-min intervals. You have also received hourly temperature data for Auckland in 2015.

You are asked to please complete the following 2 parts of analysis:

Part 1: The customer connections team is helping a property developer to size infrastructure for a new residential development and wants to know what the load as a group may look like and what variations may be expected. They ask you to determine a typical daily load profile(s) (24 hours from midnight to midnight) for Winter and Summer at aggregate level. Please comment in the script on how you chose to define typical and why.

Part 2: The customer connections team also considers asking the developer to put additional insulation into certain houses but given the current budget constraints due to COVID-19, it knows that the developer can only do this for the houses with the highest gain. Please determine the 10% of customers who will benefit the most.

The analysis can be found in the attached notebook and the full project can be found in the github repo here.

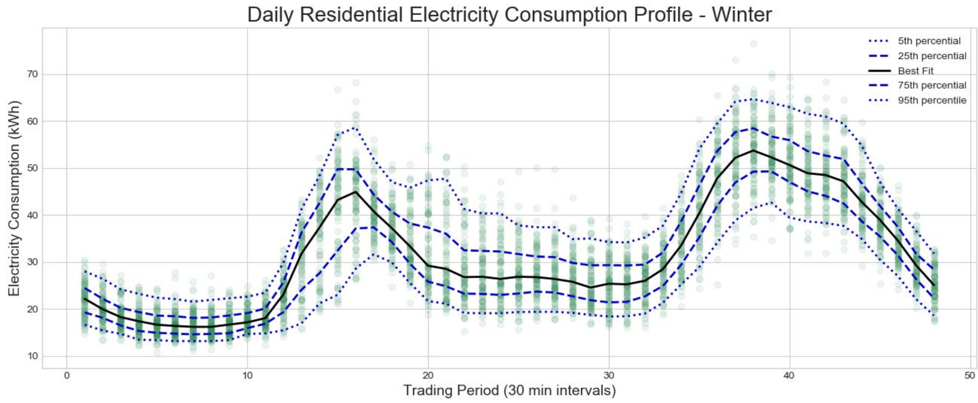
Part 1: Determining Typical Electricity Daily Load Profiles

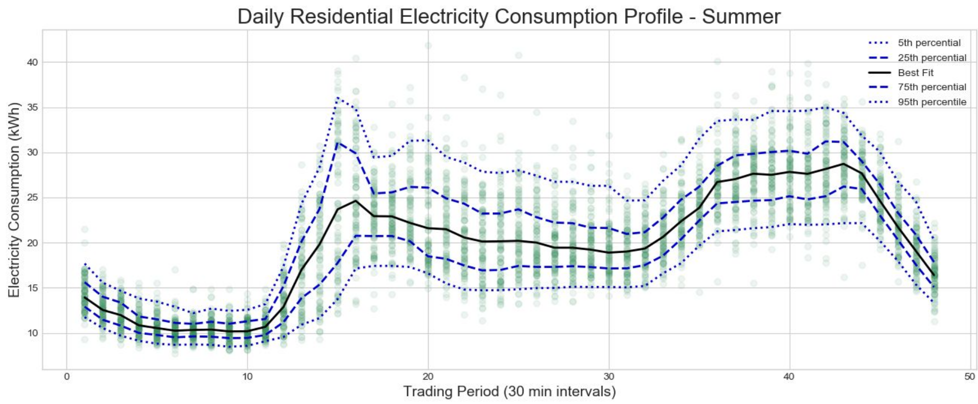
For this analysis I've described a "typical" daily load profile to be the best fit of a gradient boosted regressor model to the data. This is modelled on an aggregation across all 50 sampled installation control point (ICP) keys for all data over the Summer and Winter periods. The expected variations in the profiles are captured with quantile gradient boosted regressions at the 5th, 25th, 75th and 95th percentiles.

Some exploration was done on the possibility of removing outliers or selecting a subset (such as weekdays with public holidays removed) for the typical profile but it was not included in the final analysis because the outliers will inform the variations captured in the quantile envelopes.

The daily load profiles can be seen in the figures below and show significantly more consumption in Winter with clear peaks in the mornings and evenings as expected (before and after work).

These profiles could be used to determine the infrastructure required to meet service level agreements e.g. The ability to reliably meet the samples daily peak usage over Winter to the 95% percentile of ~65kWh.





Part 2: Determine The Most Beneficial Customers For Insulation

In order to find the "houses with the highest gain" or "who will benefit the most" a definition of gain and benefit in this context needs to be established.

While the overall reduction in electricity consumption is desirable I will assert that it is not as important as the number of people and specifically how many vulnerable people (young, elderly, comorbidities [asthma, diabetes...], etc.) would be positively impacted by having insulation installed. Also, it may turn out that the less wealthy households (maybe the ones with more vulnerable people or dependents) have tried to save money on their electricity bills and, therefore, the historical meter data will not show the benefits that those households would get.

A thorough and holistic approach would be to collect additional data such as, internal temperature and socio-demographic information (number of people, age, income, expenses, etc). The household's temperature dependent electricity consumption could then be modelled (with non-linear feature dependence) and decomposed to find the electricity consumption required to maintain a comfortable temperature while removing the impacts of socio-demographic factors such as income and expenses. The benefits could then be weighted to account for the number of people or more specifically the number of vulnerable people affected.

Given that the data provided (or readily obtainable) does not contain this information I've reframed the problem to be: identifying the households that have the highest temperature-dependent electricity consumption (this is what the insulation will theoretically reduce).

To address this reframed problem with the data available the following methodology was employed:

To align the time scale and metric types in the meter and temperature datasets a pchip interpolation and mean aggregation was applied to the temperature dataset to find the average temperature for each trading period before merging them into a single dataframe.

From there two separate approaches were tried:

- Firstly, a very simple calculation of the difference in consumption between Summer and Winter periods for each household. This is a naive solution as discussed in the attached notebook.

- Secondly, a model of the electricity consumption was constructed for each household, using a random forest regressor, before applying SHAP analysis (reference SHAP: https://github.com/slundberg/shap) to isolate the impact of temperature. This is a more complete method and goes some way in addressing the flaws of the simple calculation as discussed in the attached notebook.

Of the sets of 5 households returned by each method described above (5 being 10% of the 50 households sampled) 4 households appeared in both sets which was reassuring. However, due to the shortcomings in the difference calculation **I would recommend that the property developer insulate the households most similar to the ones returned by the SHAP dependence method (With the ICP Keys 6016463, 6016524, 6015713, 6113779 and 6406908)**.

The figure below shows a complete comparison of the results of the two methods and can be seen in more detail in the attached ipython notebook.