2024

The International Mathematics Modelling Competition

1 Summary Sheet

Pets bring us comfort and joy so it is vital that they are cared for and protected. Unfortunately, more than 10% of pets are abandoned or returned. Our team's mission was to develop a model that evaluates how ready households are to adopt to ensure that pets find loving homes. Limited to 10 inputs, we chose factors for our model which impact the physical and mental wellbeing of animals.

Each factor was assessed separately, against the expectations for pet owners we found from a variety of online sources. These expectations were defined quantitatively by 'reference points', which included a minimum, neutral and maximum value for each function. Using code and different function types, we created 'factor-specific' formulas which could accurately map the shape of the reference points, allowing us to produce a score between 0 and 1 for each factor. These values were then multiplied to give a final readiness score, to ensure that households are fairly competent in each factor before deeming them to be pet ready. Our cutoff value for readiness was 0.1, which is an objective score because our reference points and formulas were based off of this value.

We then created data for seven artificial Australian households, four of which represented typical demographics that responsibly own pets and three which should not own pets for various reasons, using them to test our model, which produced expected readiness scores for each household. Next we determined how many households are pet ready in three countries: Australia, Singapore and Norway. Our strategy was to find data on the mean and standard deviation values for every factor and country, then use our code to generate 100,000 households in each region based on this. Their values for each factor were put into our formula, giving us the readiness score of 100,000 typical households in each country and hence the percentage of households deemed 'pet ready'.

For question 2, we generalised our model to account for four additional pet species: dogs, horses, fish, and birds. Because of the efficacy of our model, this meant finding new reference points for each factor and each animal, then generating new factor-specific formulas. Our revised model then assessed six of the previously created households for readiness to own these new pets and achieved realistic values. Our model also accounts for multiple pets by calculating a readiness score for each pet the household wants to adopt, then multiplying all the scores to produce an overall score.

For part 3, we started by making trendlines for all the factors in each country and projecting it to get future data. Proxies were used for some factors when no past data could be found. We then ran 100,000 simulations for each country, obtaining the number of pet ready people in 5, 10 and 15 years. This was compared to online data on pet ownership trends which predicted how many households would adopt pets in the future, thus producing pet retention rates.

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2 Introduction

2.1 Introduction

Humans make judgements about situations by combining logic and their past experiences. In the pet industry, the experience of vets and shelter workers with households that own pets, and households that returned pets, enable them to make accurate judgements about the readiness of a household to receive a pet. The issue with this however is that the time required for a pet worker to evaluate a household is too long, so many pets are adopted by unprepared households.

To solve this, a mathematical model can be used. The purpose of models is to make judgements based purely on a limited number of numerical inputs. For the purposes of this model, we can have a maximum of just 10 inputs to ensure it can be easily used by animal shelters and pet stores. This limits the accuracy of our model compared to people, who subconsciously take into account hundreds of factors before making a choice. For this reason, it is unreasonable to expect our model to perform better than experienced workers, so our goal is to create a model that most closely matches the judgments they would make.

The goal of this model is to maximise the number of pet acquisitions and the retention rate. To determine the cutoff for readiness, a balance must be found between both these factors. Making the cutoff too high would cause few animals to be acquired, resulting in many households missing out on the benefits of owning a pet and lots of pets being euthanised or left in shelters. Alternatively, making the cutoff too low would result in either mistreatment of the animals or an elevated frequency of pets being abandoned, returned, or put up for adoption. To ensure the best possible outcome between these two extremes, we have developed our model with the most important indicators of pet readiness as inputs of our model and by testing our model with examples.

2.2 Problem Restatement

The IMMC-A, an organisation focused on pet retention and wellbeing, is asking our team to develop a quantitative model which can evaluate household readiness for cat ownership, and generalise it for different regions and animals and then to predict potential pet ownership in the future. This problem can be broken down into 4 tasks:

1. Develop a quantitative model to evaluate household readiness for ownership of cats in six or more different households within Australia.
2. Adjust the model to determine the number of households ready to own a cat in Australia, Singapore and Norway.
3. Adjust the model so that it can account for four more species (dogs, fish, horses, and birds).
4. Project the future pet demographics using the model in the next 5, 10 and 15 years.

3 Definitions and Assumptions

3.1 Definitions of Important Terms

Pet: An animal that is not owned for the economic or practical output of the animal, but rather the emotional value or the happiness they provide. In regards to the animals discussed in this report, in the case of animals such as horses which could be considered pets or not pets based on the circumstances, our report is based on the context of owning the animal as a pet.
Household: The living arrangement of an individual or a group in which they make provision for their own essentials, occurring in a single dwelling.
Ownership readiness: A measure or judgement of how capable a household is to care for a pet.
Class: A taxonomic rank, members of the same class are related. An example of a class is Mammalia which comprises all the mammal species [see 9.3.1 - A].

3.2 Considerations, Assumptions and Justifications

Assumption: The animal will not be relocated to or moved from a different country/region.
Justification: International laws for pets in transit are liable to change and should be regulated by the country/region's authority applied to pets. This further applies to required vaccinations and contamination/disease between countries.
Assumption: All developments in households, economics, and ecology remain relatively predictable in the next 15 years.
Justification: Due to rarity, freak events are deemed unnecessary to account for in our model.
Assumption: The best metric to evaluate household readiness can be determined through a purely quantitative analysis.
Justification: This will promote the user-friendly aspect of our model for the animal providers as it simplifies household readiness to a singular value.
Assumption: Garden size positively correlates to property size.
Justification: See reference [9.3.2 - A]
Assumption: The pet is happier the more time it is with the owner.
Justification: See reference [9.3.2 - B]

Consideration: Tank size for fish and cage size for bird would have significant correlation with property size and pet budget (2 of our factors, see below) so it does not have to be considered as a separate factor (also to simplify the amount of necessary inputs for our model).
Consideration: In the case of significantly different attributes between members of one species, particularly concerning different breeds of dogs, the model is tailored to the averages of these attributes across the species. These attributes include the need for attention and activity as well as amount of medical attention and food required.
Consideration: All dollar signs ($) or references to the word 'dollar' refer to Australian AUD.

3.3 List of Variables and Functions

Variable/Function and Domain	Description/Purpose
$S(x_n, g, h) = \frac{1}{1+e^{-\frac{x_n - h}{g}}}$ $x_n \in R$ normalised input value $g \in [0, \infty)$ 'gradient' of sigmoid function $h \in R$ horizontal shift	Our modified sigmoid function has a range $\in (0, 1)$. A sigmoid function was chosen
$L(x, a, v) = v + (1 - v)a^{-x}$ $x \in [0, \infty)$ input value $a \in [1, \infty)$ dilation of exponential function $v \in [0, 1]$ vertical shift of function	Used to calculate score for length dependent factors with a horizontal asymptote.
n_{dr}	Normalised data range - interchangeable variable (defined as two) and used to restrict the domain input for S(x, g, h), x in the set [0, n_{dr}]. Training the model with standardised data making for faster and more precise calculation.
$Norm(x, \alpha, \beta) = n_{dr} \cdot \frac{x-\alpha}{\beta}$ $x \in R$ input value $\alpha \in R$ input shift $\beta \in R$ input scaling	Alpha and Beta values will be calculated from the training data points, creating a shift and scaling value specific for that factor. From the calculated values, the domain $x \in [0, n_{dr}]$ will result in range [0.02, 0.98].
n_f	Number of factor-specific formulas multiplied to produce final household readiness score
$SFA(x, mass, mass_{avg}, ratio)$ $= (1 - ratio) \cdot x + ratio \cdot x \cdot \frac{mass_{avg}}{mass}$ $x \in R$ input factor value $mass \in R^+$ mass of pet $mass_{avg} \in R^+$ average mass of pet $ratio \in [0, 1]$ proportion of factor affected by mass	Size Factor Adjustment Function (SFA Function)
$s_n \in [0, 1]$	The output for the nth factor-specific formula.
i_n	i is the input for a factor n specifies which factor (the nth factor)

4 Development of Model (Q1)

4.1 Factors of the Model and their Justifications

Factor	Justification
Sum of the capability of occupants	The capability of occupants includes their capacity to interact and care for the pet. As most households include multiple people (caretakers for the pet) and responsibility for the pet can thus be shared, the sum of the capability of occupants will reflect the general capability a household has caring over a pet(s). Note that to input the sum of the capability of the occupants, each occupant would have to rate themself in terms of capability on a scale of 0.1-1 using a scale outlined in Appendix 8.3.1. An individual occupant's score depends on both their mental and physical condition: if they have both a physical and mental condition, they multiply their scores together (this accounts for the compounded effects of having both types of disabilities).
Annual budget per Pet	The annual budget per pet is the amount of money the household is prepared to spend on each pet per year, expenses would include shelter, food, healthcare and toys. Higher budgets mean the pets would be better looked after, as well as possible caretaking of the pet from a third party.
Criminal record (number of priors for specific crimes)	This includes past crimes which may reflect a negative impact on the pet's wellbeing, such as animal abuse or domestic violence. Domestic violence is included because there is significant correlation between domestic violence and animal abuse, see reference [9.4.1 - A].
Distance from nearest bushland area in km	The distance to the nearest park creates a better environment for walking dogs, and a larger space for cats to roam. This also accounts for protected bushland and heritage sites which may negatively affect household ownership, if cats/birds disrupt the native wildlife.
Property size in metres squared	This includes the size of the area where the pet can roam inside the homeowners property.
Average time at home per week in hours	This accounts for the time at least one of the occupants living at the household is at home with the ability of caring for the pet. The longer amount of time an owner is at home, the greater the wellbeing of the pet (see assumptions).
Size of pet	This factor does not directly affect readiness but does affect the other factors such as the size of the pet largely determines the cost of its food, the space it requires and the difficulty of caring for the pet.

Time to nearest vet in minutes	The time taken for a pet owner to arrive at the nearest vet determines how quickly pets could receive urgent medical attention, as well as convenience for regular checkups.
Previous ownership of a pet in the same class [see 3.1]	Previous ownership of a similar pet translates to improved ability to care and maintain the new pet.
Time dedicated to pet per day (minutes)	The time a pet receives specific attention from their owner(s), for their mental wellbeing.

4.2 Formulas for each Factor and their Justifications

4.2.1 Process for Creating Factor-Specific Formulas

Our model is based on formulas for each factor that return a score between 0 and 1. These scores are then multiplied together to return a final readiness score (see 4.3). The functions chosen for each factor as the foundation of the factor-specific formula are justified below.

Factor	Function	Reasoning
Sum of the capability of occupants	Sigmoid	A sigmoid function is used for all of these factors, as we reasoned that all factors should have horizontal asymptotes at exceptionally poor and good values for each factor. This is because increasing/decreasing passed these values would not significantly affect the pet's safety or wellbeing. Using the example of property size, 300 metres squared would be considered a very good property size for owning a cat as the cat would have lots of space to move around. Larger property sizes are not considered significantly better as the cats do not require more space, hence the horizontal asymptote at the ideal score of 1. Additionally, having only 30 metres squared of space is very suboptimal and returns a score close to 0. This amount of space is already very bad for the cat's wellbeing and further decreasing property size should not affect the score, hence the horizontal asymptote at 0. Additionally, sigmoid functions were considered because their middle section between the two asymptotes can be dilated to different levels of steepness, allowing us to account for how some factors greatly affect the pet's wellbeing with small changes (e.g. a difference of 30 square metres in property size) while other factors such as capability of occupants affect the pet's wellbeing at a slower rate, represented by a less steep middle section of the function.
Annual budget per Pet		
Average time at home per week in hours		
Property size in metres squared		
Previous ownership of a pet in the same class		
Time		

dedicated to pet per day (minutes)		Finally, we used code (see 8.4) to generate the sigmoid functions based on 3* data points specific to each factor (see 8.3.1): a 'minimum', 'neutral' and 'maximum' value (see 8.3.1 for exceptions). The minimum value for a factor corresponds to an output of 0.1 (for example inputting a property size of 18 metres squared gives an output of 0.1) and we used this as a reference point for our sigmoid functions because this is what is considered unacceptable. The only way a household would be ready to own a pet with this condition is if all their other inputs are ideal (if their output for one factor is 0.1 they require an output of 1 for all the other factors to get a final readiness score of 0.1, the cutoff, see 4.3). Neutral values correspond to values we consider average e.g. a budget of $1700/year and this would return an output of 0.79, because this is the tenth** root of 0.1. This means that if all factors returned a neutral value it would give the minimum cutoff. Maximum values correspond to the perfect output of 1.
Criminal record (animal abuse or domestic violence priors)	Sigmoid reflected over y-axis	The sigmoid function for criminal record is very steep as the input only accepts integers and even 1 or 2 convictions of animal abuse would make a household very unsuitable for owning a pet. Additionally, the sigmoid function is decreasing over our input domain ($x \geq 0$) as unlike with the other factors, a lower input is better. This function is actually still the other sigmoid function when normalised but with a negative scaling value.
Time to nearest vet in minutes	Exponential reflected over y-axis	Similar to the other factors, we believe that at a certain distance/time from the vet or bushland area, it is already not quite bad for your pet:a household being either 50 km or 500 km away from a vet would not affect the cat much as both cases are very bad. Therefore there is a horizontal asymptote for the lower value of 0. However, for the upper values, there can be a very big difference between being 500 metres from a vet and 20 metres away in the case of an emergency, so there is no horizontal asymptote for the upper value of 1. An exponential function reflected twofold was the best mathematical representation of this reasoning. Additionally, similar to the sigmoid functions we transformed the exponential functions using code (see 8.4) so that it best matched 'minimum', 'neutral' and 'maximum' points* (see 8.3.1)
Distance from nearest bushland area (m)		
Size of pet (kg)	No factor-specific function	Size of pet is an input whose effects can be accounted for by adjusting three other factors (sum of occupants' capability, pet budget and property size). See below for more details.

*Additional points apart from the 'minimum', 'neutral' and 'maximum' points were used for some of the factors (see 8.3.1), returning outputs such as 0.5 or 0.9. These were calculated using information from the same sources that informed our 'minimum', 'neutral' and 'maximum' points and these additional points were added when additional points improved the function generated by our code (see 8.4), providing a more accurate function (see 8.4 for error % calculation).

**The tenth root is used as a neutral value despite there being nine factors that produce outputs to calculate the final readiness score, because without this adjustment a completely average household would only just be ready for a pet and this is unlikely to reflect reality or promote adoption of pets.

Transformations of Functions

To ensure that most households can achieve the required readiness score which we set as 0.1, many of the functions had to be dilated or translated to asymptote at certain values or so that average households would be able to score a value of 0.79.

Our model also accounts for differences in the importance of factors through the dilation of the functions. For cats, we considered the household's pet budget to be more important than distance to bushland, so distance to bushland had an asymptote at the neutral value instead of 0 so that it had less of an impact on a household's final readiness score. There are similar adjustments for some other factors (see 8.3.1).

Pet Size

As previously stated, pet size is an input whose effects can be measured by adjusting other factors. This is represented in our model, not by changing our factor-specific formulas, but by adjusting the input before the factor-specific formula is applied. Providing an example, for a 6kg cat which is over the average weight of 4kg, an input of $1200 for pet budget is reduced to a lower number before being put into our factor-specific formula, returning a lower score for that factor without having to adjust our formula. Details on how this is mathematically achieved are below.

The factors affected are property size, pet budget and sum of capability.

Property size and sum of capability are adjusted mathematically by multiplying the input for these two factors by the average pet weight/inputted pet weight and then inputting this new value into the function*** (the functions for these two factors are increasing functions so there are no problems with sign or having average and inputted pet weight the wrong way around).

Budget is adjusted differently in our model because we reasoned that having a bigger pet increases the amount of money spent on food, but not on toys or medical needs. Because approximately half of the average pet budget is spent on food [see reference 9.4.2 - A], pet size only adjusts half of the pet budget (for cats, so this half will be represented by the variable $ratio$). Mathematically, this is represented by the Size Factor Adjustment Function outlined in 3.3 (x = pet budget input):

$$(1 - ratio) \cdot pet\ budget\ input + ratio \cdot pet\ budget\ input \cdot \frac{mass\ avg}{mass}$$

Where the first term is the unaffected proportion of the inputted value and the second term is the affected proportion of the input times the original adjustment of average weight over input weight.

***For our code, the pet size adjusts property size and capability of occupants using the Size Factor Adjustment Function but with a $ratio$ value of 1.

4.2.2 Factor-Specific Formulas

The following section contains the factor-specific formula and their transformation values.
Transformation value **g** changes the gradient of the sigmoid function.
Transformation value **h** changes the horizontal translation of the sigmoid function.
Transformation value **a** changes the vertical dilation of the exponential function.
Transformation value **v** changes the vertical translation of the exponential function.
Scaling and shift values can be found in 8.3.1.

<table>
<tr><th>Factor</th><th>Formula</th><th>Transformation Values (4dp)</th></tr>
<tr><td>Sum of the capability of occupants</td><td rowspan="7">$$\frac{1}{1+e^{-\frac{x-h}{g}}}$$
*Though criminal record is represented by a sigmoid function reflected in the y-axis unlike the other factors, the general formula is the same because a negative g value is sufficient to reflect the equation. The reason the g value for criminal record is not negative however is because the scale input for the normalised sigmoid function is negative (see 8.3.1).</td><td>g: 0.1126
h: 0.6479</td></tr>
<tr><td>Annual budget per Pet</td><td>g: 0.2390
h: 1.1170</td></tr>
<tr><td>Average time at home per week in hours</td><td>g: 0.1631
h: 0.5637</td></tr>
<tr><td>Property size in metres squared</td><td>g: 0.0600
h: 0.1321</td></tr>
<tr><td>Previous ownership of a pet in the same class</td><td>g: 0.8087
h: -1.0947</td></tr>
<tr><td>Time dedicated to pet per day (minutes)</td><td>g: 0.3461
h: 0.4780</td></tr>
<tr><td>Criminal record (animal abuse or domestic violence priors)*</td><td>g: 0.2310
h: 1.3164</td></tr>
<tr><td>Time to nearest vet in minutes</td><td rowspan="2">$$v+(1-v)\,a^{-x}$$</td><td>a: 1.0225
v: 0.5</td></tr>
<tr><td>Distance from nearest bushland area (m)</td><td>a: 1.0050
v: 0.7943</td></tr>
</table>

Generation of Factor Specific Variables

To determine the best values for the factor specific variables, a training process was undertaken in code. This was done by starting with some initial values for g and h, or a and v for the functions and then calculating an error score by finding the difference in expected values for each score and the ideal values and squaring it. $Error = (point_y - f(point_x, a, b))^2$ The sum of these values is then used as a total error score, where the lower the difference in actual values and expected values, the lower the error score. By then making small random changes and then comparing error score to the current values it can be determined if the change in the values is an improvement more closely approximating the ideal function. By then repeating this until no further improvements are made and the error value is low then we can be sure that the function is a close approximation to the ideal values.

4.3 Combining the Formulas to create the General Model

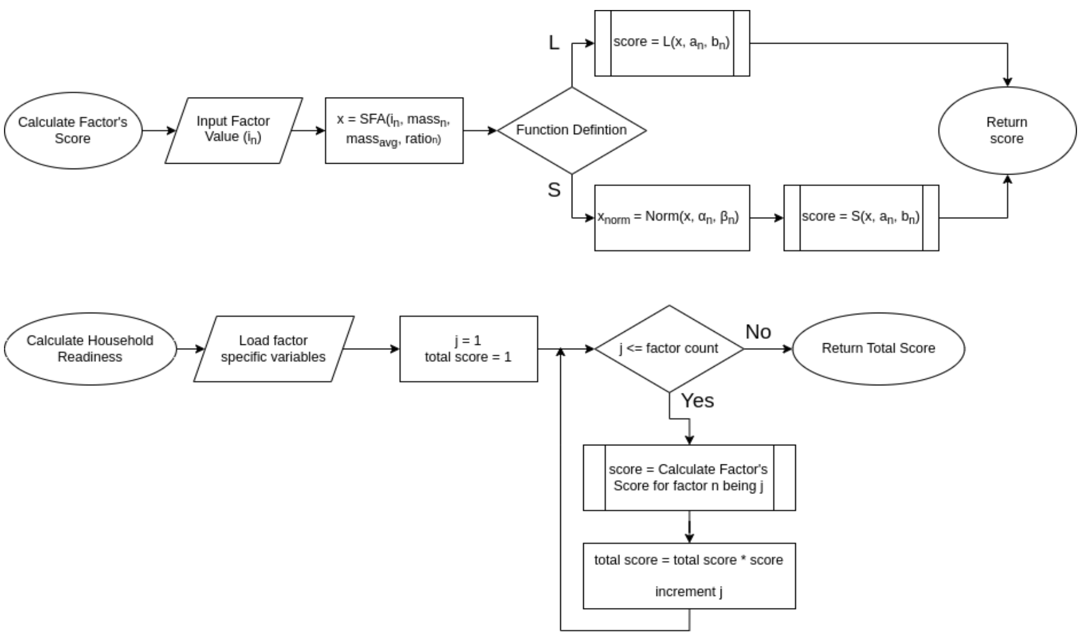
General model

A household's overall readiness score is a combination of the outputs from all the factor-specific formulas. The outputs from all the factor-specific formulas are multiplied together to produce a final output which will be between 0 and 1 like the outputs from the factor-specific formulas. If this final output is above 0.1, the household is deemed to be ready for pet ownership.

Note: The inputs for pet budget and time dedicated to pet are expected to change for each household based on the pet they are considering adopting, because different species require very different amounts of time and money, for example, even if a household is willing to spend $3000 dollars on their dog, though it would be in their budget to do the same for their fish, it is unrealistic for them to spend this amount on a fish.

$$Total\ Score = \prod_{1}^{n_f} s_n \qquad \begin{array}{l} Total\ Score \geq 0.1 \implies \text{Household is ready} \\ Total\ Score < 0.1 \implies \text{Household is not ready} \end{array}$$

Diagram of process



Justifications and reasoning

Simple multiplication of all the outputs from the factor-specific formulas was chosen as our final model to calculate household readiness score because of simplicity and efficacy. Weighting factors differently based on importance does not have to be included in our overall model because it is accounted for by the difference in gradient of the functions used for the factor-specific formulas. Additionally, combining the outputs through multiplications ensures that if any of the pet's factor inputs are unsuitable for the pet, the household is immediately disqualified regardless of how ideal the other factor inputs may be. Consider a cat living in an almost ideal household, except the owner is never at home. The cat may have food and be well-looked after, but its well-being would be very poor and the cat would be very unhappy. By multiplying all the factors together, we ensure that any one very unsuitable input immediately renders a household 'unready'.

Limitations and strengths of the model

The main limitations of the model is that it is very dependent on the reference points used to generate the sigmoid and exponential functions used for the factor-specific formulas, which cannot be accurate for all scenarios and also require more research to be accurately determined. Additionally the model is limited because it assumes pets of the same species and size cost the same amount of money to maintain and it cannot account for any of the differences between dog breeds (such as temperament) except for size.

The strengths of the model are that it is easy to apply to other species because the actual model does not have to change at all, simply the reference values are changed based on sources and then the code can generate new transformative values for the sigmoid functions which can account for differences in the importance of each factor between species. Additionally, the model's simplicity renders it very easy to use by any type of animal provider and it is also very easy for households to input their information if this model were to be converted to a survey. Finally, a great strength of the model is that it also can be very easily modified to account for household readiness of multiple pets (see 5.3).

4.4 Testing of Model Part 1 (Four Acceptable Households)

Note: All these households are located in Australia, our chosen region. Also, see Appendix 8.3.2 for specific data values attributed to each household with justifications.

	Household 1	Household 2	Household 3	Household 4
Description	A single elderly person who needs a walking frame and is living in the suburbs on a pension.	Traditional middle class family with two kids that lives in the suburbs. Both parents work a 9-5 and the kids are in primary school.	High income family, parents are busy with work and aren't home until late. They live in a big house and have a kid in primary school.	Single person with a severe disability, however they are looked after by a carer. They live in a small granny flat but are always home.
Readiness Score (4dp)	0.1219	0.3688	0.1789	0.1264

Significance of Examples

<u>Household 1</u> - The elderly are a class of people we want to ensure can largely qualify for owning a cat. It is known that owning pets is vital for improving the quality of life for this demographic as they prevent loneliness and depression which result from decreased social activity. A cat is an ideal pet for them as cats are low maintenance, affordable and provide companionship. Ensuring that our model allows most elderly people to get a cat is therefore vital. This was done by creating a model household that is realistic for elderly people in terms of their many hours spent at home and giving the cat attention, while also having fairly low inputs for factors such as pet budget and checking that it would be successful.

<u>Household 2</u> - The 'traditional' middle class family is ideal for cat ownership, as they will usually have one or two stable jobs that will be able to comfortably support a cat and they will be home often enough to build a strong bond together. Additionally, having pets has been shown to have a positive impact on kids [See 9.8.3 - Q]. Our model should therefore score this group highly to reflect their compatibility.

<u>Household 3</u> - High income earners are generally more busy, meaning they have less time to spend with their pet. A family of three with two busy parents may not be well suited to certain pets such as dogs, however due to cats being lower maintenance, they should qualify for owning a cat. Despite their weaknesses when it comes to time spent at home and with their pet, this is generally made up for with a larger house and more money to spend on their pet.

<u>Household 4</u> - Although people who have a severe mental disability cannot care for a cat themselves, with the help of a full time carer they should be eligible to own one. Although not having a job decreases their yearly budget for their cat, they have much more time to care for the cat which usually makes up for this.

4.5 Testing of Model Part 2 (Three Not Acceptable Households)

Note: All these households are located in Australia, our chosen region. Also, see Appendix 8.3.3 for specific data values attributed to each household with justifications.

	Household 5	Household 6	Household 7
Description	Wealthy couple who live in a rich suburb and own their own business. They have had 3 animal abuse charges.	Young couple who are rarely home due to work. No kids and they live in a small 1 bedroom apartment, trying to save money.	Unemployed young person who rents in small motels.
Readiness Score (4dp)	0.0458	0.0188	0.0328

Significance of Examples

Household 5 - People who have had repeat animal abuse charges should not be able to own an animal in the vast majority of scenarios to protect the wellbeing of the cat. This example shows the strictness of our model when it comes to this factor, as this couple that performs reasonably in most other factors is brought down by their 2 animal abuse charges.

Household 6 - Having low factor scores in one area can be made up in other areas, shown in the examples above, however this is an example of a household that has low factor scores in multiple areas and this disqualifies them from owning a cat. In addition to being busy which causes them to not be home often and spend minimal time with their cat, they live in a small apartment with a tight budget for their cat. This combination of factors will disqualify a household in most scenarios.

Household 7 - An unemployed person in many cases is not in a position to start owning a cat. These scenarios arise when their financial situation doesn't allow them to look after the cat well to the point where the extra time they spend at home can't make up for it.

4.6 Calculating Number of Ready Households in Chosen Regions

We have picked three different countries with different laws, incomes and demographics to show how our model can be applied to a variety of different regions:

Australia: High income with densely urban, residential, and rural areas, and varying climate with some restrictive laws. The population of Australia is 26.6 million people [see reference 9.4.6 - A].
Singapore: High population density and public housing, more restrictive laws on pet ownership. The population of Singapore is 6 million people [see reference 9.4.6 - B].
Norway: Cooler climate, residential and rural areas, and fewer restrictive laws on pet ownership. The population of Norway is 5.5 million people (see reference 9.4.6 - C).

Calculating the number of ready households posed a challenge to our initial model, as data on specific households is not available, only general data about the whole population on a factor-by-factor basis. Our solution: given the mean and standard deviation for each of our selected variables, and assuming a neutral result for distance_to_park and time_to_vet as data could not be found for these variables, the inputs for 100000 houses were randomly generated reflecting the above found data. Each of these houses were then run through our model with the total score plotted on frequency histograms found in Appendix 8.3.4.

Note: In the table below, SD refers to the standard deviation of the collected data.

	Australia	Singapore	Norway
Sum of Capability of Occupants (average capability score of 0.9 per person)	Mean occupants: 2.52 Mean sum of capability: 2.268 SD: 0.655 [See 9.4.6 - D]	Mean occupants: 3.15 Mean sum of capability: 2.835 SD: 0.655 [9.4.6 - E]	Mean occupants: 2.11 Mean sum of capability:1.899 SD: 0.655 [See 9.4.6 - F]
Annual Budget Per Pet ($)	Mean: $1715 SD: $311 [See 9.4.6 - G]	Mean: $2150 SD: $324 [See 9.4.6 - H]	Mean: $1213 SD: $198 [See 9.4.6 - I]
Criminal Record (number of Animal Abuse and domestic violence convictions)	No specific data on deviation so for the purposes of our model, we assumed this to be on average 0, a realistic assumption because all the actual averages were all below 0.05. [See 9.4.6 - J][See 9.4.6 - K][See 9.4.6 - L][See 9.4.6 - M] [See 9.4.6 - N]		
Distance from nearest bushland (m)	Factor is ignored due to lack of information (one of the limitations of this process is the data available).		

Property size (square metres)	Mean: 467 SD: 148 [See 9.4.6 - O]	Mean: 85 (mostly apartments) SD: 50 [See 9.4.6 - P]	Mean: 122 SD: 41 [See 9.4.6 - Q]
Time at home per week in hours	Mean: 38 SD: 11 [See 9.4.6 - R]	Mean: 36 SD: 10 [See 9.4.6 - S]	Mean: 42 SD: 7 [See 9.4.6 - T]
Time to Nearest Vet (minutes)	Factor is ignored due to lack of information (one of the limitations of this process is the data available).		
Previous ownership of pet in the same class	Mean: 1.3 SD: 0.3	Mean: 0.9 SD: 0.2	Mean: 1.1 SD: 0.25
Time spent with pet per day (minutes)	Mean: 35 SD: 20 [See 9.4.6 - U]	Mean: 40 SD: 15 [See 9.4.6 - V]	Mean: 45 SD: 15 [See 9.4.6 - W]
Population of country	26,600,000	6,000,000	5,500,000
Average number of people per household	2.52 [See 9.4.6 - D]	3.15 [9.4.6 - E]	2.11 [See 9.4.6 - F]
Number of households	10,555,555	1,904,762	2,606,635
Percentage of Houses ready (3dp)	88.732%	77.803%	89.281%
Number of households deemed 'pet ready'	9,366,155	1,481,962	2,327,230

A limitation of this new model is that the neutral values and the above data changes depending on the type of pet so new tables for each pet would have to be made with new percentages and data if it were to be generalised for more pet types. Also factors are assumed to be normally distributed which is reasonable for most factors but not necessarily accurate. Additionally lots of data could not be found so some factors could not be considered and they had no weighting on the model. Finally, the 100,000 houses do not necessarily reflect reality but it is a large enough sample to make the amount of error negligible.

5 Generalisation of Model (Q2)

5.1 Generalisation of Model for Four Additional Species

Dogs: Dogs are the most common pet in the world, and as such should be included in our model so it can be maximised in the most circumstances.
Horses: Horses are primarily in rural areas due to their large accommodation requirements, optimising our model such that it can account for larger barnyard animals.
Fish: Fish require tanks and as such do not need large property size or a significant owner presence, incentivising us to adapt our model to remove these factors. Furthermore, larger fish species may require higher maintenance costs and space.
Birds: Birds are usually kept in cages, but need regular maintenance and are able to fly outside if permitted by the given region. However, taking into consideration the wellbeing of the bird inside a cramped cage, ethical adjustments to our model will promote animal welfare through assessments on the suitability of the bird's accommodation.

The most significant modification to our model to account for additional species is generating new sigmoid and exponential functions for our factor-specific formulas based on new reference points. This is because for most of the factors the values change significantly based on how important that factor is for the species. To use the sum of capability of occupants as an example, dogs and horses are more active and difficult to manage than cats, so household's need to be more capable to be deemed ready for dog and horse ownership, hence the reference points would be different and the transformative values for our factor-specific formulas are different. The **new reference points for each species with their justifications can be found in 8.3.5.**

Additionally, some factors were deemed void for some species, particularly for fish which require less care, so these factors are ignored completely for that species (indicated by red cells in the table below and in the table in Appendix 8.3.5, justified in Appendix 8.3.5). This changes the neutral output value as less factors are being considered, so the neutral value was lower for fish, horses and birds. The final consideration was for the Size-Factor Adjustment Function which can be applied to other species but using new values for the average pet weight for each species (in 8.3.5).

Transformative values for all the factor-specific formulas based on species are below (to 4dp):

Factor	Function Type	Dog	Fish	Horse	Bird
Sum of the capability of occupants	Sigmoid	g: 0.2218 h: 1.0960	g: 0.1609 h: 0.9255	g: 0.1127 h: 1.1811	g: 0.1409 h: 0.8096

Annual budget per Pet		g: 0.4996 h: 0.8045	g: 1.0325 h: 0.0489	g: 0.6091 h: 0.4930	g: 0.8487 h: -0.0421
Criminal record (number of priors for specific crimes)		g: 0.2309 h: 1.3163	g: 0.2981 h: 0.6648	g: 0.2312 h: 1.3161	g: 0.2306 h: 1.3162
Time dedicated to pet per day (minutes)		g: 0.4058 h: 0.5577	g: 0.4304 h: -0.6280	g: 0.1811 h: 0.6238	g: 0.4145 h: -0.1969
Property size in metres squared		g: 0.0801 h: 0.1647		g: 0.1944 h: 0.4272	
Average time at home per week in hours		g: 0.1562 h: 0.8611	g: 0.0239 h: 0.2535	g: 0.1552 h: 0.5347	g: 0.1114 h: 0.4255
Previous ownership of a pet		g: 0.8088 h: -1.0948	g: 0.8089 h: -1.0950	g: 0.2530 h: -0.2195	g: 0.8088 h: -1.0948
Time to nearest vet in minutes	Exponential	a: 1.0225 v: 0.5000		a: 1.0046 v: 0.4000	a: 1.0225 v: 0.5000
Distance from nearest park/bushland area in km		a: 1.0003 v: 0.7943			

5.2 Applying the Model to Six Households

Note: The model is applied to the first six households outlined in 4.4 and 4.5. To see their descriptions and the significance of using each household as an example, see 4.4 and 4.5. See Appendix 8.3.2 and 8.3.3 for specific data values attributed to each household. Adjustments to their budget and are below, size of pet for these species have been kept at the average to clearly show the impact of other factors. Additionally, each household is modified to have had 1 of these pets previously as this reflects pet ownership in Australia.

	H1	H2	H3	H4	H5	H6
Budget per pet	Dog: \$1000 Horse: \$1500 Fish: \$70 Bird: \$150	Dog: \$2459 Horse: \$3000 Fish: \$100 Bird: \$250	Dog: \$4000 Horse: \$7000 Fish: \$150 Bird: \$400	Dog: \$1000 Horse: \$1500 Fish: \$70 Bird: \$150	Dog: \$4000 Horse: \$7000 Fish: \$150 Bird: \$400	Dog: \$1200 Horse: \$1750 Fish: \$75 Bird: \$160

H=household	H1	H2	H3	H4	H5	H6
Score (Dog)	0.0107	0.2065	0.0310	0.0179	0.0394	0.0003
Score (Horse)	0.0001	0.0165	0.0092	0.0086	0.0044	0.0011
Score (Fish)	0.5217	0.6542	0.7467	0.5446	0.3871	0.5682
Score (Bird)	0.4440	0.5280	0.6125	0.4635	0.0451	0.4350

Note: Green indicates household readiness (a score of 0.1 or higher) and red indicates the household is not ready for pet ownership (a score of lower than 0.1).

Justification of Results

These households were designed for cat ownership and also had some poor values to show how our model promotes pet ownership. However, this means when the households are assessed for dog or horse ownership (more demanding animals), the households performed poorly. Also as expected, the households scored highly for fish and birds because they are easier to look after.

5.3 Accounting for Multiple Pets

A simple yet effective method to adapt our formula to multiple pets is to calculate the total score for each individual pet and then multiply all of these resulting total scores and then use this value as the new total score and ensure it is above the minimum requirement.

Example:

If you want to have three pets you would calculate a total score for each first:

Pet 1: 0.534 Pet 2: 0.463 Pet 3: 0.764

The product of all of these values is 0.1888, which is higher than the cutoff value of 0.1. This means that they can have those 3 pets. If however, they adopted another pet of value: 0.475, the new total would be 0.0897, which is below the cutoff. An advantage of this solution is that you can easily account for multiple pets, as all pets have a total score that is directly comparable due to the selection score being equal between the models for the animals.

Other Considerations

Additionally, the budget per pet formula does not have to be changed because it is an input so households can input a lower value for this if their budget is reduced to adopt multiple pets. Our model also accounts for differences in ease of caring for different species (e.g. taking care of 100 fish is easier than 100 horses), simply because using our model it is much easier to get a high readiness score for a fish than for a horse (lower input values still translate to a higher score).

6 Application of Model (Q3)

6.1 Model for Future Pet Readiness

To calculate projected pet ownership and retention rate in the next 5, 10 and 15 years, the readiness of each population at these time intervals needed to be known. As our model calculates readiness based on input factors such as pet budget and property size, these input factors need to be calculated for the future dates. These factors change over time, so the future values were estimated by extrapolating past data from a trend line. Once the input values for each time interval in each country were determined, they were fed into our model and a readiness score calculated for each country and animal (to 2dp).

Australia	Cat	Dog	Bird	Fish	Horse
2024	88.70%	68.04%	99.47%	99.73%	0.01%
2029	88.80%	67.92%	99.52%	99.74%	0.01%
2034	89.70%	66.90%	99.61%	99.77%	0.01%
2039	88.83%	64.54%	99.58%	99.79%	0.01%

Singapore	Cat	Dog	Bird	Fish	Horse
2024	77.57%	1.59%	99.83%	99.88%	0.01%
2029	78.51%	1.77%	99.87%	99.92%	0.01%
2034	78.95%	1.93%	99.90%	99.94%	0.01%
2039	79.42%	2.19%	99.94%	99.96%	0.01%

Norway	Cat	Dog	Bird	Fish	Horse
2024	94.25%	55.07%	99.39%	99.37%	0.01%
2029	95.01%	58.83%	99.48%	99.39%	0.01%
2034	95.78%	61.79%	99.46%	99.43%	0.01%
2039	96.40%	64.13%	99.49%	99.42%	0.02%

Note: the low eligibility for people in Singapore to own dogs is not representative of the current amount of dogs owned in Singapore. This can be attributed to our model valuing property size and how the small properties that are common in Singapore are not well suited for dogs.

6.2 Pet Retention Rates

Both the retention rates and ownership of pets are closely tied to the readiness of the population, as a population that can better look after their pets will be more able to get pets and less likely to abandon them. It therefore follows that a population that undergoes a rise in readiness will experience a proportional increase in retention rates and total pet ownership (e.g. if the pet readiness of Norway increases by 1%, the retention rate and acquisition of pets will also rise by 1%)

Retention rate graphs

Note: the values in the boxes represent the **percentage change** in the pet retention rate from 2024, not pet retention rate because there was no information available for the current pet retention rate.

Australia	Cat	Dog	Bird	Fish	Horse
2029	0.11%	-0.18%	0.05%	0.01%	0%
2034	1.13%	-1.68%	0.14%	0.04%	0%
2039	0.15%	-5.15%	0.11%	0.06%	0%

Singapore	Cat	Dog	Bird	Fish	Horse
2029	1.21%	11.32%	0.04%	0.02%	0%
2034	1.78%	21.38%	0.07%	0.06%	0%
2039	2.38%	37.74%	0.11%	0.05%	0%

Norway	Cat	Dog	Bird	Fish	Horse
2029	0.81%	6.83%	0.09%	0.02%	0%
2034	1.62%	12.2%	0.07%	0.06%	0%
2039	2.28%	16.45%	0.1%	0.05%	0%

Pet ownership (thousands)

Note: As both pet retention and pet ownership are both proportionally affected by readiness value, the effect of this table is multiplying the change in readiness value (or retention rate as they are the same) by the number of pets owned in 2024

Australia	Cat	Dog	Bird	Fish	Horse
2024	5300 (see A)	6400 (see B)	5600 (see C)	11200 (see D)	1000 (see E)
2029	5306	5290	5303	5301	1000
2034	5360	5211	5307	5302	1000
2039	5308	5027	5306	5303	1000

Singapore	Cat	Dog	Bird	Fish	Horse
2024	114 (see F)	94 (see G)	Not available	Not available	Not available
2029	115	105	0.04%	0.02%	0%
2034	116	114	0.07%	0.06%	0%
2039	117	129	0.11%	0.05%	0%

Norway	Cat	Dog	Bird	Fish	Horse
2024	783 (see H)	490 (see H)	195 (see H)	Not available	Not available
2029	789	523	195	0.02%	0%
2034	796	550	195	0.06%	0%
2039	801	571	195	0.05%	0%

Note: Where starting pet populations were not available, percentage changes in pet populations were used instead.

7 Letter to the Decision Makers

Dear Directors of the IMMC-A,
Thank you for giving us this opportunity to further your mission to maintain and care for pets internationally. Our goal of increasing the number of pet owners and improving pet retention rate will benefit the mental and physical health of pets and their owners worldwide. Pets help their owners exercise, socialise and feel love. The owners love them in return, and care for their wellbeing through visits to the vet, giving them their attention and more. In matching potential pets with new pet owners on an international scale, we can significantly improve the amount of beautiful relationships between animals and humans.

To achieve this goal, we have formulated a model which effectively matches potential pets and capable households, ensuring that more pets leave shelters for homes, and stay there. This model has been created with practicality and objectivity in mind, producing a simple numerical rating for each household on a scale from 0 to 1, so that it can be quickly used to determine whether a household should be considered for pet ownership.

Though the model was trained on data for five pet species and three countries, the model would be very effective for other animals and regions because it can be easily adapted for more pet species and more regions with some data that could easily be collected by local animal providers. This means that the model could quickly and effectively be implemented by shelters and animal providers worldwide, assessing millions of households to ensure that pets around the globe find safe and loving homes.

Animal welfare is of utmost importance to us and truly believe that the world can benefit from the model we have provided. Our recommendation is its immediate widespread use so that pets around the world can reap the rewards it can offer and find loving homes as soon as possible.

Best Wishes,
2024002

8 Appendix

8.1 AI Use Report

No AI was used in the creation of our model or the writing of this report.

8.2 Consideration of Laws in Specific Countries

Animal/ Country	Australia	Singapore	Norway
Cat	No restrictive laws except around protected areas	No cats allowed in public housing (80% of the population live in public housing) [see 9.8.2 - A] The Singaporean government would ensure no households living in public housing would be able to own a cat. No impact on our model.	No restrictive laws
Dog	Some dog breeds are not allowed, but this has no impact on our model as the government/animal providers would prevent adoption of these breeds, so ownership readiness is irrelevant	Some dog breeds are not allowed, but this has no impact on our model as the government/animal providers would prevent adoption of these breeds, so ownership readiness is irrelevant	No restrictive laws
Fish	No restrictive laws	Some species are not allowed, but this has no impact on our model as the government/animal providers would prevent adoption of these species, so ownership readiness is irrelevant	No restrictive laws
Horse	There is a minimum paddock size of 4000 square metres in Australia [see 9.8.2 - B] However, the government would ensure that only people who own a paddock of this size would be allowed to own a horse. No	Horses in Singapore must be kept at a facility separate to one's household. [see 9.8.2 - C] The Singaporean government would prevent household's from purchasing a horse unless they owned a separate facility. No	No restrictive laws

	impact on our model.	impact on our model.	
Bird	No restrictive laws	For captive-bred birds, caged birds can be let out, as long as they are not causing a disturbance. [see 9.8.2 - D] Insignificant impact so not accounted for in the model (doesn't significantly affect quality of life when birds make a disturbance and non captive-bred birds are unlikely to be considered as pets).	No restrictive laws

8.3 Calculations and Data

8.3.1 Data and Graphs for Factor-Specific Formulas (Cat Ownership Model)

Reference points for factor-specific formulas (including justifications)

Note: Min refers to an output of 0.1
Neutral refers to an output of 0.77
Max refers to an output of 1

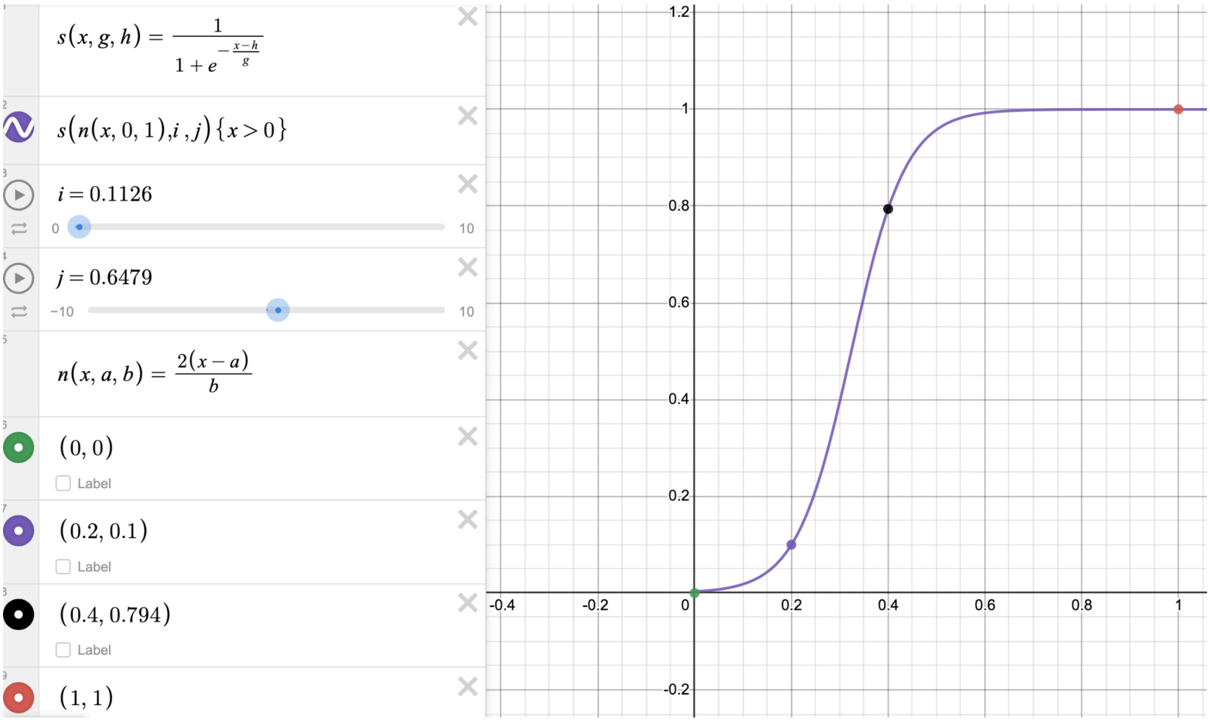
Factor	Reference Points (Output: Input)	Justifications
Capability of Occupants	Min: 0.2 Neutral: 0.4 Max: 2	Min: Bed bound occupants unlikely to be capable of caring for a cat Neutral: Someone in a wheelchair can look after a cat well Max: Perfect mobility equates to being able to look after your pet very well
Annual Budget Per Pet ($)	Min: 600 Neutral: 1440 0.9: 1715 Max: 2016	Min: Only spending money on food costs this much, which is not ideal for your pet at all [See 9.8.3 - A] Neutral: This is equivalent to spending a reasonable/average

		amount of money for food, toys and grooming) [See 9.8.3 - B] 0.9: Average money spent annually on a cat in Australia [See 9.8.3 - C] Max: This is an above average and spending more money on toys and food would not benefit the cat
Criminal Record	Min: 2 0.5: 1 Max: 0	Min: These many instances of abuse means that the person is not suitable for owning a pet as the cat would not be safe 0.5: This should have a significant negative effect on a person's readiness score as pet safety is really important Max: No prior convictions is ideal
Distance from nearest bushland (metres)	Neutral: 1000 0.8: 500 0.85: 300 0.9: 100 Max: 40	Neutral: Cats unlike to make it to the bushland but should not significantly affect readiness as cats do not necessarily require bushland for their wellbeing 0.8: Cats can rarely make their way to the bushland from the household 0.85: Some cats can make their way to the bushland from the household 0.9: Most cats can easily make their way to the bushland from the household Max: Cats can easily make their way to the bushland from the household [See 9.8.3 - D] [See 9.8.3 - E]
Property Size (square metres)	Min: 18 Neutral: 80 Max: 600	Min: Minimum amount of space a cat needs to stay healthy but very suboptimal [See 9.8.3 - F] Neutral: Sufficient space to not affect the cat's wellbeing [See 9.8.3 - G] Max: Lots of space is ideal for your cat so that it can roam freely throughout the property [See 9.8.3 - H] [See 9.8.3 - I]
Time spent at home (hours per week)	Min: 7 Neutral: 28 0.9: 49 Max: 72	Min: Cat will survive as long as you are at home for at least one hour per day to feed the cat and make sure it is okay, but this is a suboptimal situation Neutral: Four hours a day is sufficient to ensure your cat doesn't get lonely 0.9: Seven hours per day on average is beneficial for the cat's wellbeing Max: Any more time than 10 hours spent at home would not improve the cat's wellbeing or safety

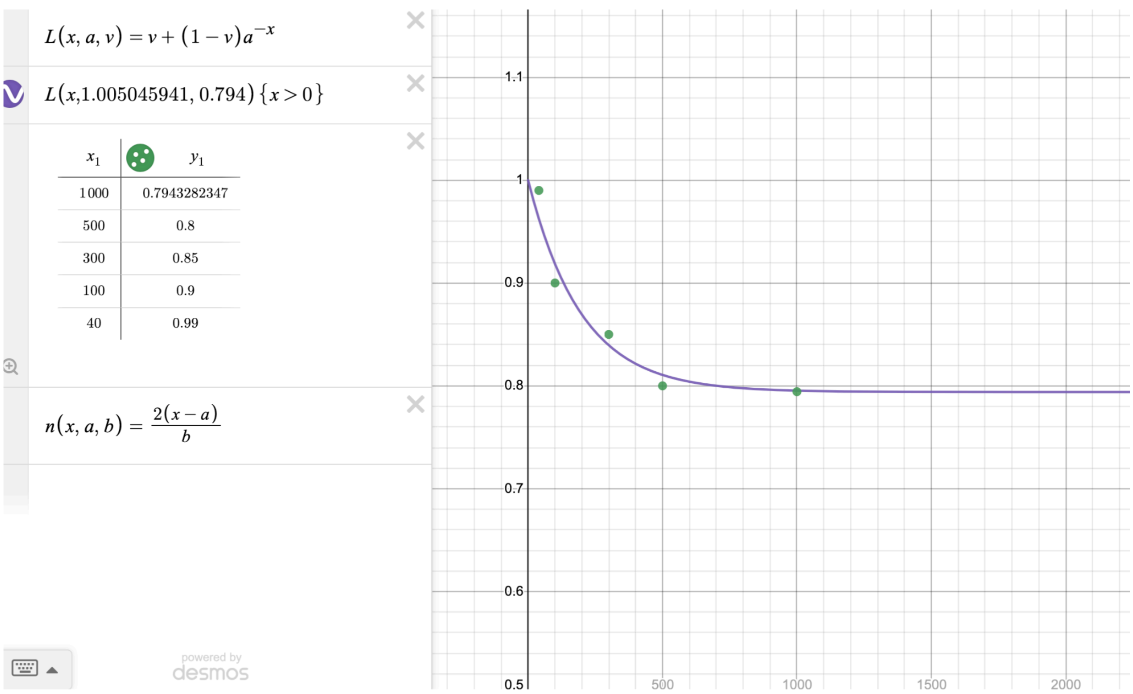
Time to nearest Vet (minutes)	0.5: 90 Neutral: 30 Max: 5	0.5: An hour and a half from a vet is not ideal for the cat's physical wellbeing Neutral: Thirty minutes is average Max: Being within five minutes of a vet is ideal [See 9.8.3 - J]
Previous ownership of pet	Neutral: 0 0.9: 1 0.95: 2 Max: 3	Neutral: Not having had this pet before should not reduce a household's readiness score 0.9: Having some experience with this pet is beneficial 0.95: Having more experience with this pet is greatly beneficial Max: Having lots of experience with this pet is greatly beneficial
Time dedicated to pet (minutes)	0.2: 5 0.3: 10 Neutral: 30 Max: 60	0.2: Not ideal for the cats mental wellbeing whatsoever, but cats are fairly independent so they would survive with this amount of attention 0.3: See above Neutral: Average amount of time dedicated to a pet in a household [See 9.8.3 - K] Max: Very beneficial amount of attention for cats, anymore is not necessary as cats are fairly independent [See 9.8.3 - L]
Size of pet (kg)	Average size of a cat was set at 4.5kg	[See 9.8.3 - M]

Example Factor-Specific Formula Graphs (Reference points included)

Capability of Occupants



Distance to bushland



Factor	Function	a	b	scale	shift	error
Capability	s	0.1125961651	0.6479022584	1	0	0.001014699321
Pet Budget	s	0.2389711308	1.116941598	2016	0	0.07608246266
Distance To Park	l	1.005045941	0.7943282347			0.1330861809
Property Size	s	0.06002765666	0.1320565753	582	18	0.00001463046393
Time At Home	s	0.1631091998	0.5637023368	72	0	0.9571964733
Criminal Record	s	0.2310085774	1.316343103	-3	3	0.4651270529
Time To Vet	l	1.022508826	0.5			0.8758666664
Previous Ownership	s	0.8086626702	-1.094684941	3	0	0.001211612344
Time Dedicated	s	0.3461206457	0.4780250844	55	5	0.01567972189

Above: Table with information on each factor-specific formula including function type (see below, s corresponds to sigmoid and l to exponential), the transformation values (a corresponds to g and a, b corresponds to h and v), error percentage (deviation of the formula generated by the code from the reference points), scale and shift (see explanation below).

Normalisation of Inputs

To make the data more manageable and to work better with our code, the training data is normalised. This is done by finding all the training data in the format (input, score) with score values between 0.02 and 0.98 and then projecting the x values of these values onto the domain 0 to 2. This is done through the function $Norm(x, shift,\ scale)$ where x is the input value.

To calculate scale:

The coordinate with the largest score within 0.02 and 0.98 is found (c_{max}) and similarly the coordinate with smallest score is found (c_{min}). Scale is then calculated through the difference in x values: $(c_{max})_x - (c_{min})_x$.

The shift is then calculated as $min(c_{min},\ c_{max})$

Function Types

For functions using the ‘s’ function:

$score\ = S(Norm(x, shift,\ scale),\ a,\ b)$

For functions using the ‘l’ function:

$score\ = L(x,\ a,\ b)$

Note: These equations should be used to visualise the graph

Scale for sum of capability of occupants

The capability of a person is dependent on their physical and mental condition as well as their age [see 9.8.3 - N] [see 9.8.3 - O].

Rating	Description
0.2	Physical: Bed bound Mental: Severely mentally ill Kids: 0-3
0.4	Physical: Wheelchair Mental: Moderately ill Kids: 4-6
0.5	Physical: walking frame Mental: Moderately ill Kids: 7-8
0.6	Physical: Crutches Mental: Mildly ill Kids: 9-10
0.8	Physical: Sticks Mental: Very mildly ill 11-12
0.9	Physical: Independant on some surfaces Mental: Mild symptoms of suboptimal cognitive function 13-15
1	Physical: Independant on all surfaces Mental: No mental illness Kids: 16+

8.3.2 Data for Three Acceptable Households

Household 1 (Single elderly person):

Factor	Value	Factor Score	Justification
Size of pet	5kg	N/A	This is an above average weight, to show how a larger cat can affect other factors and to represent a suboptimal scenario.
Sum of capability of occupants	0.5	0.9037	This is the value for someone using a walking frame , which is generally the lower bound for elderly people's mobility (excluding wheelchair).
Annual budget per pet	$950	0.2827	This is far below the average spend of $1715 per year, which means this is the likely budget for elderly people with a tight budget such as the pension.
Criminal record (Animal abuse or domestic violence)	0 convictions	0.98	It is generally unlikely that an elderly person would be convicted of such an offence, however if they were, they would need to perform higher than this example to qualify. This is reasonable as having a higher budget or two people in the house would make up most of the difference).
Nearest park/bushland	3km	0.7943	Elderly people commonly live in suburban areas, which have a high park density so 3km would be further away than average.
Property size	$140m^2$	0.9817	This is generally on the low end of retirement properties according to sources: [See 9.8.3 - P]
Average time at home/week (awake)	70h	0.9998	Due to retirement, elderly people will be at home much more than people who are still working, which improves the strength of the relationship between them and the cat.
Time to nearest vet	20 minutes	0.8204	This is higher than average while still being reasonable for a suburban region.
Previous ownership of a pet in the same class	0	0.7943	This shows that owning a pet is not needed for elderly people to be able to easily acquire a cat.
Time dedicated to pet	60 minutes	0.9878	This is an input that elderly people would be above average for, as they have more time to dedicate to their cat.

Household 2 (Middle class family):

Factor	Value	Factor Score	Justification
Size of pet	6kg	N/A	This shows that despite increased costs due to a higher weight, this family is still able to easily qualify for owning a cat.
Sum of capability of occupants	3.1	1	This is made up of two capable parents (2) as well as two kids aged 7 (0.5) and 10 (0.6).
Annual budget per pet	$1715	0.8232	This is the average amount households spend on cats in Australia.https://kb.rspca.org.au/knowledge-base/how-many-pets-are-there-in-australia/
Criminal record (Animal abuse or domestic violence)	0	0.9507	This is realistic for the average household.
Nearest park/bushland	2km	0.7943	This is reflective of high park density in suburban areas
Property size	242m^2	0.9992	This is a reasonable property size Australia
Average time at home/week (awake)	69.5h	0.9998	This is the average time people spend at home https://flowingdata.com/2021/09/03/everything-more-from-home/
Time to nearest vet	30 mins	0.7564	This shows that even if a household is far away from a vet, they can still get a cat due to their beneficial other factors.
Previous ownership of a pet in the same class	0	0.7947	Although 92% of Australians have owned a pet, this is ensuring that they still can get a cat if it is their first.
Time dedicated to pet	60 minutes	0.9878	This is one of the strengths of 'traditional' households is they can tend to their pet well as both the kids and parents have time to play with their pet.

Household 3 (high-income family):

Factor	Value	Factor Score	Justification
Size of pet	4.5kg	N/A	This is the average weight of a cat and does not affect other factors.

Sum of capability of occupants	2.5	1	This is made up of two capable parents (2) and one 8 year old child (0.5).
Annual budget per pet	$2016	0.9758	Although this class of family does not spend lots of time at home, their high income allows them to look after their cat well financially.
Criminal record (Animal abuse or domestic violence)	0	0.9507	This is representative of most households.
Nearest park/bushland	6km	0.7943	As they live in a high density area, there is a high chance they are not located near a park.
Property size	700m^2	1	Reflective of their high income, as they could likely afford a large house despite living in an expensive area.
Average time at home/week (awake)	28hr	0.7879	Despite being busy, they are still likely to spend 4 waking hours in the house each day on average.
Time to nearest vet	20 minutes	0.8204	This is a reasonable time for a high density area.
Previous ownership of a pet in the same class	1	0.8982	This is likely as 92% of Australians have owned a pet.
Time dedicated to pet	15 minutes	0.4181	This would be one of the downsides of this class of household, however this is made up in other areas.

Household 4 (Disabled person with a carer):

Factor	Value	Factor Score	Justification
Size of pet	4.5	N/A	This is the average weight of a cat and does not affect other factors.
Sum of capability of occupants	1.2	1	One capable carer (1) and a severely mentally ill person (0.2)
Annual budget per pet	$900	0.2813	As they won't be able to have a job, their pet budget will be far below average
Criminal record (Animal abuse or domestic violence)	0	0.7943	It is unlikely that someone with a severe mental disability would have a criminal record

Nearest park/bushland	2km	0.7943	Reasonable distance for low density suburbs
Property size	100m^2	0.9237	Due to the inability to work, they are unlikely to have money for a large house. Consequently, they are likely to live either in a small granny flat or community centre. [See 9.8.3 - R]
Average time at home/week (awake)	70 hours	0.9998	Someone with a severe disability is unlikely to leave the house much, so 10 hours per day on average is a good estimate.
Time to nearest vet	20 minutes	0.8204	Reasonable distance for low density suburbs.
Previous ownership of a pet in the same class	0	0.7947	Owning cats is less common for this group of people
Time dedicated to pet	60 minutes	0.9878	As they are unlikely to have a job, they will be able to spend a large amount of time with their cat

8.3.3 Data for Three Not Acceptable Households

Household 5 (Couple with animal abuse priors):

Factor	Value	Factor Score	Justification
Size of pet	3	N/A	This was chosen to show that even with a smaller pet that
Sum of capability of occupants	2	1	Two capable adults
Annual budget per pet	$2000	0.9968	Due to their successful business they are able to spend large amounts of money on their pet.
Criminal record (Animal abuse or domestic violence)	2	0.0567	N/A
Nearest park/bushland	100m	0.9187	This factor is showcasing that even in the best case scenario people with 2 criminal charges are barred from owning a pet.

Property size	$1000m^2$	1	Due to their successful business they own a large property.
Average time at home/week (awake)	48h	0.9912	As their business has taken off, they have more time to relax as they have outsourced some of the jobs of running the business.
Time to nearest vet	5 mins	0.9473	Same reason as nearest park/bushland
Previous ownership of a pet in the same class	2	0.9527	Due to their 2 previous abuse charges
Time dedicated to pet	60 minutes	0.9878	Same reason as nearest park/bushland

Household 6 (young couple who wants to save money and are out a lot):

Factor	Value	Factor Score	Justification
Size of pet	4.5	N/A	This is the average weight of a cat and does not affect other factors.
Sum of capability of occupants	2	1	Two capable adults.
Annual budget per pet	$ 1000	0.3723	This is a below average budget that would be representative of people trying to save money.
Criminal record (Animal abuse or domestic violence)	0	0.9507	This is representative of most households.
Nearest park/bushland	5km	0.7943	Living in high density urban areas means parks are further away.
Property size	$50m^2$	0.4090	This is the average size of a small 1 bedroom apartment. [See 9.5.2 - A]
Average time at home/week (awake)	21hr	0.5301	This is representative of a couple who rarely spends time at home due to work and other commitments (3hr per day)
Time to nearest vet	20min	0.8204	Reasonable distance for low high density areas.
Previous	1	0.8983	One previous cat is a reasonable figure for a young

ownership of a pet in the same class			couple, as it is likely one of them had a cat as a child.
Time dedicated to pet	15 minutes	0.4181	This is due to the couple not being home often

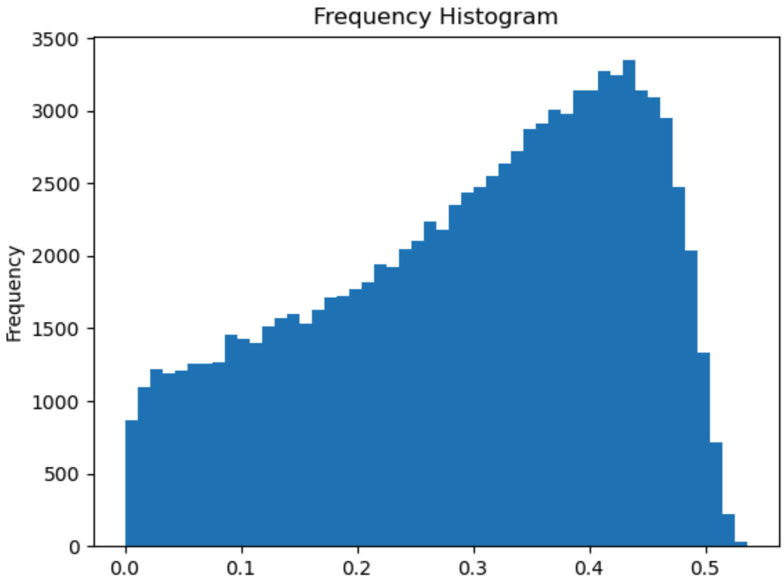
Household 7 (unemployed young person):

Factor	Value	Factor Score	Justification
Size of pet	4.5	N/A	
Sum of capability of occupants	1	1	One capable adult
Annual budget per pet	$700	0.1458	This is near the minimum budget someone in Australia can spend on a cat to meet the bare minimum for survival
Criminal record (Animal abuse or domestic violence)	0	0.9507	This is representative of most households.
Nearest park/bushland	3km	0.7943	Reasonable distance for low density suburbs
Property size	$50m^2$	0.4090	his is the average size of a small 1 bedroom apartment
Average time at home/week (awake)	70	0.9998	Due to them being unemployed, they will be home for a large portion of the day.
Time to nearest vet	20	0.8204	This is average for suburban areas.
Previous ownership of a pet in the same class	1	0.8983	Due to 93% of Australians owning a pet at some point
Time dedicated to pet	60 minutes	0.9878	Due to being unemployed, they will have time to look after their pet

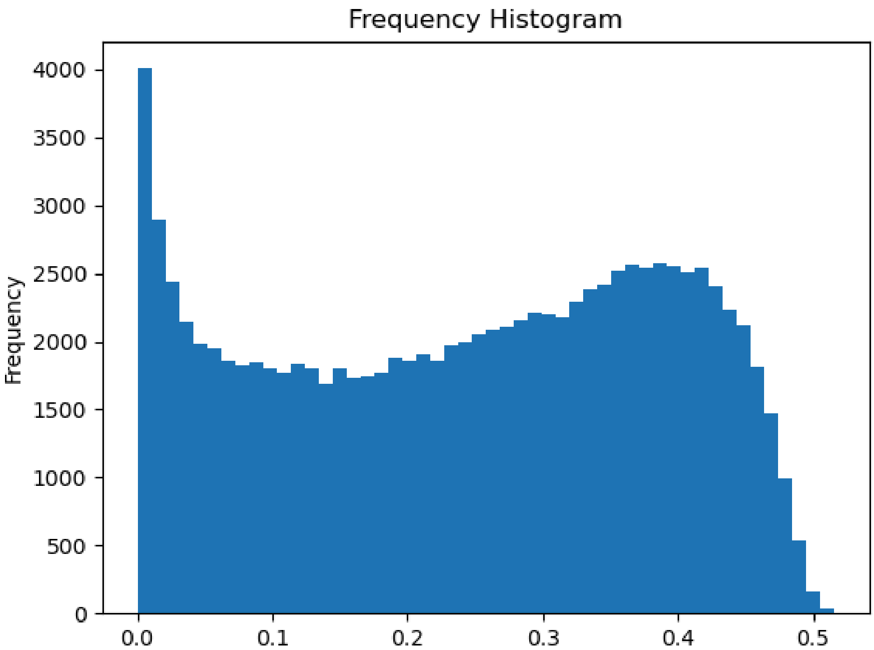
8.3.4 Graphs of the Simulations in 4.6

In all graphs the x axis represents the total score and the y axis represents the frequency this score was received out of the 100000 simulated households. These graphs show the spread of the scores for cats between countries. Note: All scores below 0.1 are considered a FAIL.

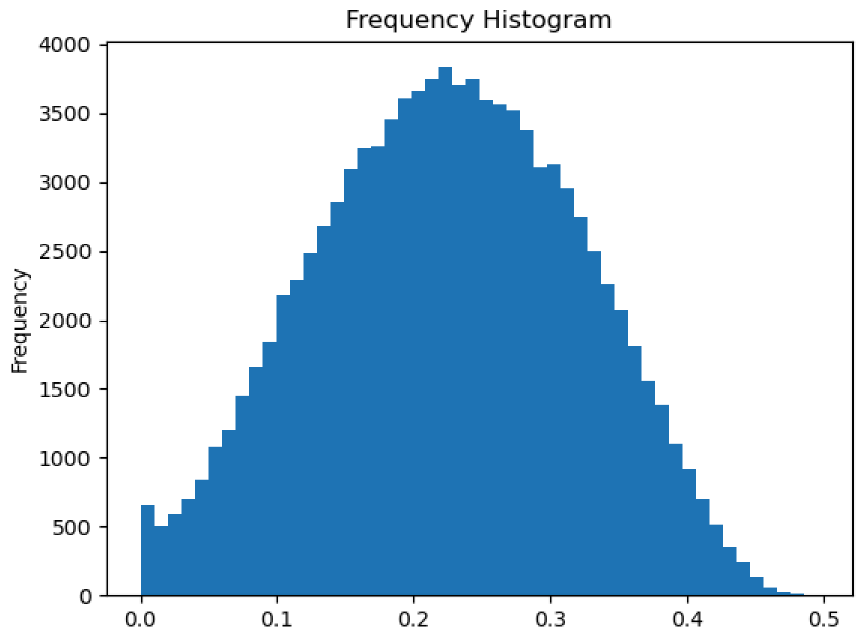
Australia



Singapore



Norway



8.3.5 Data for Species-Generalised Model

The reference points that our code used to generate the transformative values to make the factor-specific formulas for each species.

Dog

Factor	Reference Points (Output: Input)	Justifications
Capability of Occupants	Min:0.3 Neutral: 0.7 Max: 1	Min: Mostly in a wheelchair, difficult to feed and walk dogs. Neutral: Walking Stick, a little trouble to walk a dog. Max: Fully capable body with optimal health for walking the dog.
Annual Budget Per Pet ($)	Min: 600 0.3: 910 0.9: 3218	Min: Lowest possible amount to feed an average sized dog, no accessories. 0.3: Some accessories, a larger portion to feed the dog. 0.9: Lavish portions,

Criminal Record	Min: 2 0.5: 1 Max: 0	Min: These many instances of abuse means that the person is not suitable for owning a pet as the dog would not be safe 0.5: This should have a significant negative effect on a person's readiness score as pet safety is really important Max: No prior convictions is ideal
Distance from nearest bushland (metres)	0.5: 10000 Neutral: 4000 0.9: 1000 Max: 200	0.5: A large distance - for the dog to have access to the park driving is the easiest option Neutral: Driving is still possible, but so is walking 0.9: Walking to the park is short, park is easily accessible Max: Walking to the park is extremely short
Property Size (square metres)	Min: 100 Neutral: 350 0.9: 500 Max: 2000	Min: Cramped conditions for dog to move around Neutral: Larger space for large dogs to run 0.9: Even larger space able to keep multiple dogs with comfort Max: Extreme amount of space
Time spent at home (hours per week)	Min: 21 Neutral: 42 0.9: 63 Max: 77	Min: Low amount of owner presence affecting the dog's welfare Neutral: Larger owner presence, still insufficient for the dog's wellbeing 0.9: Sufficient time to make sure the dog won't get lonely Max: Any more time allocated than 11 hours per day is unnecessary
Time to nearest Vet (minutes)	0.5: 90 Neutral: 30 Max: 5	0.5: An hour and a half from a vet is not ideal for the dog's physical wellbeing Neutral: Thirty minutes is average Max: Being within five minutes of a vet is ideal
Previous ownership of pet	Neutral: 0 0.9: 1 0.95: 2 Max: 3	Neutral: No other pet should still have a benign affect to the ownership of a dog 0.9: Previous ownership is beneficial 0.95: 2 prior ownerships greatly increases suitability Max: Any more dogs is deemed unnecessary
Time dedicated to pet (minutes)	0.2: 15 0.5: 30 Neutral: 45 Max: 70	0.2: Dogs are more sociable animals, and thus need more attention - 15 minutes is insufficient 0.5: 30 minutes should have a beneficial effect Neutral: Should be enough time to feed and walk a dog Max: Extremely beneficial to feed, walk, and play with the pet dog
Average size of pet (kg)	18.4	[See 9.8.3 - V]

Horse

Factor	Reference Points (Output: Input)	Justifications
Capability of Occupants	Min: 0.7 Neutral: 1 Max: 1.5	Min: Capability should be high for feeding, grooming, and maintaining horse and its enclosure Neutral: One person of optimal fitness will be more beneficial to horse Max: Multiple people is optimal for maintaining a horse
Annual Budget Per Pet ($)	0.3: 1200 0.7: 4000 0.9: 7000	0.3: Minimum requirement for purely feeding and housing the horse - if grass is readily available 0.7: Including costs for medication and vaccinations the horse might require to ensure the highest welfare 0.9: Maximum maintenance to ensure optimal wellbeing
Criminal Record	Min: 2 0.5: 1 Max: 0	Min: These many instances of abuse means that the person is not suitable for owning a pet as the horse would not be safe 0.5: This should have a significant negative effect on a person's readiness score as pet safety is really important Max: No prior convictions is ideal
Distance from nearest bushland (metres)		Horses do not require parks or bushland for their mental wellbeing
Property Size (square metres)	Min: 500 Neutral: 3000 Max: 8000	Min: minimum size for horse to graze, outside food is required and low space means the horse cannot move freely Neutral: Larger space for single horse, still harder for multiple horses to fit comfortably Max: Extremely large space for horses to graze and move around freely.
Time spent at home (hours per week)	Min: 0 Neutral: 14 0.9: 28 Max: 49	Min: Time needs to be allocated such that the horse can be given water, food, and housing Neutral: 2 hours a day has a positive effect on horse's wellbeing. 0.9: Large owner presence maximises horse's wellbeing

Time to nearest Vet (minutes)	0.4: 500 0.6: 240 Neutral: 120 Max: 0	0.3: 500 minutes is a very long time for a vet to get to the horse, but this factor should not immediately disqualify many rural households that are this distance from a vet 0.5: As the vet usually goes to the horse, should not be a large issue Neutral: Shorter time for vet travel, should decrease costs Max: Being closer to a vet is ideal
Previous ownership of pet	0.7: 0 0.85: 1 0.95: 3 Max: 10	0.7: Horse ownership requires menial labour and attention which may be harder for a primary buyer 0.85: Prior experience greatly increases owner suitability Max: Used for rural farms where multiple horses are extremely common - indicates proficiency in ownership
Time dedicated to pet (minutes)	0: 0 Neutral: 75 0.9: 120 Max: 180	Min: Time needs to be allocated such that the horse can be given water, food, and housing Neutral: Minimum amount of time dedicated to feeding and housing the horse 0.9: More time to groom the horse Max: Large amount of time to fulfil all of the horses requirement - beneficial to wellbeing
Average size of pet (kg)	550kg	[See 9.8.3 - S]

Bird

Factor	Reference Points (Output: Input)	Justifications
Capability of Occupants	Min: 0.2 Neutral: 0.4 Max: 0.8	Min: Little attention is required to feed the bird Neutral: Larger mobility increases capacity to play and interact with the bird Max: Should be enough to
Annual Budget Per Pet ($)	0.5: 75 0.7: 160 0.9: 360	0.5: Minimum amount required to feed the bird only 0.7: Larger amount to properly feed as well as some medical checkups 0.9: Healthcare and vaccinations accessible

Criminal Record	Min: 2 0.5: 1 Max: 0	Min: These many instances of abuse means that the person is not suitable for owning a pet as the bird would not be safe 0.5: This should have a significant negative effect on a person's readiness score as pet safety is really important Max: No prior convictions is ideal
Distance from nearest bushland (metres)		Birds do not require parks or bushland for their mental wellbeing
Property Size (square metres)		The bird will unlikely have access to the entire house, they will be kept in their cage mostly and the size of their cage is likely proportional to their owner's budget
Time spent at home (hours per week)	Min: 0 Neutral: 7 0.9: 28 Max: 49	Min: Time is needed to feed the pet bird Neutral: Minimum time allocated to increase pet's wellbeing 0.9: Larger amount of time to ensure bird's welfare Max: Maximum amount
Time to nearest Vet (minutes)	0.5: 90 Neutral: 30 Max: 5	0.5: Large amount of time for the bird to be in transit Neutral: Lower amount of time for the bird in emergency situations Max: Small amount of time is beneficial
Previous ownership of pet	0.9: 0 0.95: 1 0.98: 2 Max: 3	0.9: Low amount of past experience needed for owning a pet 0.95: Prior experience indicates high benefits for the bird Max: Larger amount of experience maximises welfare
Time dedicated to pet (minutes)	0.6: 3 0.8: 7 0.9: 15 Max: 30	0.6: minimum amount of time to feed bird 0.8: larger time to clean cage 0.9: time to play with the bird and release from cage, increasing welfare Max: maximum time to feed and play with bird
Average size of pet (kg)	0.35	[See 9.8.3 - T]

Fish

Factor	Reference Points (Output: Input)	Justifications
Capability of Occupants	Min: 0.2 Neutral: 0.4 Max: 0.7	Min: Minimum mobility required to feed fish Neutral: Greater mobility to clean fish tank 0.7: Maximum capability needed to maintain fish environment
Annual Budget Per Pet ($)	0.5: 40 0.7: 75 0.9: 104	0.5: Bare minimum required to feed a single fish 0.7: Larger amount to ensure high water quality 0.9: Optimal amount to maintain fish wellbeing
Criminal Record	Min: 3 0.5: 2 Max: 0	Min: These many instances of abuse means that the person is not suitable for owning a pet as the fish would not be safe 0.5: This should have a significant negative effect on a person's readiness score as pet safety is really important Max: No prior convictions is ideal
Distance from nearest bushland (metres)		Fish do not require parks or bushland for their mental wellbeing
Property Size (square metres)		The fish will not have access to the entire house, they will be kept in their tank and the size of their tank is likely proportional to their owner's budget
Time spent at home (hours per week)	Min: 0 Neutral: 7 0.95: 28 Max: 49	Min: Time is needed to feed the pet fish Neutral: 1 hour a week should ensure fish safety Max: Maximum amount of time to optimise fish welfare
Time to nearest Vet (minutes)		Fish are not attended to by vets, in the occasion of a medical emergency fish usually simply die
Previous ownership of pet	Neutral: 0 0.9: 10 0.95: 20 0.98: 30 Max: 50	Neutral: Some experience needed to regulate water purity and cleanliness of fish tank 0.95: Multiple fish owned previously indicates higher suitability: Max: A large amount of fish maximises score
Time dedicated to pet (minutes)	0.8: 1 0.9: 2 0.95: 5 Max: 10	0.8: small amount of time dedicated to make sure fish is reasonable 0.9: Larger amount to maintain fish tank 0.95: Larger amount of time to feed/pet fish

		Max: Maximum amount of time to optimise fish welfare
Average size of pet (kg)	0.03	[See 9.8.3 - U]

Size Factor Adjustment Ratio Value

	Dog	Horse	Fish	Bird
Capability	0.5	0.5	0	0
Property Size	1	1	0	0
Budget per pet	0.51	0.51	0.8	0.8

8.3.6 Data for Model of Future Pet Ownership

To model future pet ownership and retention rates, we used our adapted model for population readiness rates for a given location. We did this by retrieving data for each of our selected locations for the current year. We then extrapolated data using trend lines for the factors that would change over time, of most importance; property size, time at home and time dedicated to pet. However to then do this for all animal types would have been too time consuming so a compromise was made to approximate data for each other animal based on the cat data already created for all countries. This was done through a scaling factor to which the input value for cats would be scaled to be adapted for the other pets. This scaling factor was determined through the formula $\frac{cat\ average\ value}{animal\ average\ value}$. The compromise meant that we had to make the assumption that any change in values for cats would be proportional to the change in any other animals.

		dog	bird	fish	horse	TOTAL
ENABLED		0	0	1	0	
Scaling	criminal_record	1	1	1	1	1
Scaling	distance_to_parl	1	1	1	1	1
Scaling	time_to_vet	1	1	1	1	1
Scaling	capability	1	1	1	1	1
Scaling	pet_budget	1.87638484	0.1516034985	0.05364431487	3.206997085	0.05364431487
Scaling	property_size	1	1	1	1	1
Scaling	time_at_home	1	1	1	1	1
Scaling	previous_owners	1	1	1	1	1
Scaling	time_dedicated	2	0.33333333	0.05714285714	2.142857143	0.05714285714

Australia

	2024			2029			2034			2039	
criminal_record	0	0	criminal_record	0	0	criminal_record	0	0	criminal_record	0	0
distance_to_park	mean	mean	distance_to_park	mean	mean	distance_to_park	mean	mean	distance_to_park	mean	mean
time_to_vet	mean	mean	time_to_vet	mean	mean	time_to_vet	mean	mean	time_to_vet	mean	mean
capability	2.268	0.655	capability	2.278	0.655	capability	2.288	0.655	capability	2.298	0.655
pet_budget	1715	311	pet_budget	1745	311	pet_budget	1775	311	pet_budget	1805	311
property_size	467	148	property_size	445	148	property_size	411	148	property_size	377	148
time_at_home	38	11	time_at_home	38.5	11	time_at_home	39	11	time_at_home	39.5	11
previous_ownership	1.3	0.3	previous_ownership	1.3	0.3	previous_ownership	1.3	0.3	previous_ownership	1.3	0.3
time_dedicated	35	20	time_dedicated	35	20	time_dedicated	36	20	time_dedicated	36	20

Singapore

	2024			2029			2034			2039	
criminal_record	0	0	criminal_record	0	0	criminal_record	0	0	criminal_record	0	0
distance_to_park	mean	mean	distance_to_park	mean	mean	distance_to_park	mean	mean	distance_to_park	mean	mean
time_to_vet	mean	mean	time_to_vet	mean	mean	time_to_vet	mean	mean	time_to_vet	mean	mean
capability	2.835	0.655	capability	2.835	0.655	capability	2.835	0.655	capability	2.835	0.655
pet_budget	2150	324	pet_budget	2160	324	pet_budget	2170	324	pet_budget	2180	324
property_size	85	50	property_size	85	50	property_size	84	50	property_size	84	50
time_at_home	36	10	time_at_home	37	10	time_at_home	38	10	time_at_home	39	10
previous_ownership	0.9	0.2	previous_ownership	0.9	0.2	previous_ownership	0.9	0.2	previous_ownership	0.9	0.2
time_dedicated	40	15	time_dedicated	40	15	time_dedicated	41	15	time_dedicated	41	15

Norway

	2024			2029			2034			2039	
criminal_record	0	0	criminal_record	0	0	criminal_record	0	0	criminal_record	0	0
distance_to_park	mean	mean	distance_to_park	mean	mean	distance_to_park	mean	mean	distance_to_park	mean	mean
time_to_vet	mean	mean	time_to_vet	mean	mean	time_to_vet	mean	mean	time_to_vet	mean	mean
capability	1.899	0.655	capability	1.909	0.655	capability	1.919	0.655	capability	1.929	0.655
pet_budget	1213	198	pet_budget	1233	198	pet_budget	1253	198	pet_budget	1273	198
property_size	244	61	property_size	252.6	61	property_size	259.6	61	property_size	266.6	61
time_at_home	42	7	time_at_home	41.5	7	time_at_home	41	7	time_at_home	40.5	7
previous_ownership	1.1	0.25	previous_ownership	1.1	0.25	previous_ownership	1.1	0.25	previous_ownership	1.1	0.25
time_dedicated	45	15	time_dedicated	45	15	time_dedicated	46	15	time_dedicated	46	15

8.4 Coding for Factor-Specific Formulas

All code was created in python for speed of programming and flexibility. This code should also be simple to run, relying only on pre-installed libraries (except for the creation of radar graphs and histograms). All data was inputted as either TSV files (Tab Separated Values) or in JSON.

Development of Model (Q1)

functions.py - Essential functions for the model.

```
import math


def s(x, g, h):
  if g == 0:
    if x > h:
```

```
        return 1
    elif x < h:
        return 0
    else:
        return 0.5

  power = (-(x-h)/(g))

  # python will raise an error if the power is too large
  if power > 10:
    return 0
  if power < -10:
    return 1

  return 1 / (1 + (math.e)**power)


def l(x, a, v):
  if x < 0:
    return
  if v > 1:
    return 1

  if a <= 1:
    return 1

  if -x > 20:
    return v

  return v + (1-v)*a**(-x)


def error_of_point(y, x, test_g, test_h, function):
  return (y - function(x, test_g, test_h))**2


def calc_total_error(data, test_g, test_h, function):
  total_error = 0
  for x, y in data:
    total_error += error_of_point(y, x, test_g, test_h, function)
  return total_error


def normalise_values(data: list[float]):
  x_max = max(data, key=lambda coord: coord[0])
  x_min = min(data, key=lambda coord: coord[0])

  increasing_function = x_max[1] > x_min[1]

  small_coords = [x[0] for x in data if x[1] <= 0.02]
  large_coords = [x[0] for x in data if x[1] >= 0.98]

  large_boundary = None
  small_boundary = None

  if increasing_function:
    if len(large_coords):
      large_boundary = min(large_coords)
    else:
      large_boundary = max(x[0] for x in data)
    if len(small_coords):
      small_boundary = max(small_coords)
    else:
      small_boundary = min(x[0] for x in data)
  else:
    if len(large_coords):
      large_boundary = max(large_coords)
    else:
      large_boundary = min(x[0] for x in data)
    if len(small_coords):
      small_boundary = min(small_coords)
    else:
      small_boundary = max(x[0] for x in data)

  NORMALISD_DATA_RANGE = 2

  scale = large_boundary - small_boundary
  shift = small_boundary

  cropped_coords = None

  if increasing_function:
    cropped_coords = [x for x in data if (
      x[0] <= large_boundary and x[0] >= small_boundary)]
  else:
```

```
    cropped_coords = [x for x in data if (
        x[0] >= large_boundary and x[0] <= small_boundary)]

  cropped_coords = [(NORMALISD_DATA_RANGE * (x[0] -
              shift) / scale, x[1]) for x in cropped_coords]

  return (cropped_coords, scale, shift)
```

main.py - Calculates the g and h values for each sigmoid function based on input data and the a and v values of our modified exponential function, then saving the results in model_description.json to be utilised in any calculations.

```
import math
import os
import functions
import random
import json


def calculate_g_h(data, test_function):
  current_g = {
    functions.s: 0,
    functions.l: 2
  }[test_function]
  current_h = {
    functions.s: 1,
    functions.l: min(x[1] for x in data)
  }[test_function]

  actual_iterations = 0
  improvement_iterations = 0

  current_error = functions.calc_total_error(
    data, current_g, current_h, test_function)

  itterations_without_improvement = 0

  while current_error >= 0.000001 and itterations_without_improvement < 10000 and actual_iterations <= 1000000:
    h_change_amt = 1 * (math.log2(current_error * 10 + 1) + 0.1)
    g_change_amt = 1 * (math.log2(current_error * 10 + 1) + 0.1)

    change_g = random.uniform(-g_change_amt, g_change_amt)
    test_g = current_g + change_g
    change_h = random.uniform(-h_change_amt, h_change_amt)
    test_h = current_h + change_h

    if test_function == functions.s:
      test_g = max(0, test_g)
      test_h = max(min(test_h, 4), -2)
    elif test_h:
      test_h = min(x[1] for x in data)

    error = functions.calc_total_error(
      data, test_g, test_h, test_function)
    error_change = error - current_error

    if error_change < 0:
      current_g = test_g
      current_h = test_h
      improvement_iterations += 1
      current_error = error
      itterations_without_improvement = 0

    actual_iterations += 1

  # print(f"Current Error {improvement_iterations}/{actual_iterations} {current_error}, g: {current_g}, h {current_h}")

  return (current_g, current_h, current_error)


def main():
  factors = [
    ('capability', functions.s),
    ('pet_budget', functions.s),
    ('distance_to_park', functions.l),
    ('property_size', functions.s),
    ('time_at_home', functions.s),
    ('criminal_record', functions.s),
    ('time_to_vet', functions.l),
```

```
        ('previous_ownership', functions.s),
        ('time_dedicated', functions.s)
    ]

    model_data_file = open('model_description.json')
    results = json.load(model_data_file)

    animal = input("Which animal should be values be calculated for? ")

    file_path = os.path.join('./data', 'info', f"{animal}.json")
    model_data_file = open(file_path)
    models_list = json.load(model_data_file)

    results[animal] = {
        "info": models_list
    }

    for factor, test_function in factors:
        file_path = os.path.join('./data', factor, f"{animal}.tsv")
        if not os.path.exists(file_path):
            continue

        tsv_file = open(file_path)
        data = []
        for line in tsv_file:
            x, y = line.split('\t')
            data.append((float(x), float(y)))

        normalised_coords, coord_scale, coord_shift = functions.normalise_values(
            data) if functions.s == test_function else (data, None, None)

        g, h, error = calculate_g_h(normalised_coords, test_function)

        results[animal][factor] = {
            "function": test_function.__name__,
            "a": g,
            "b": h,
            "scale": coord_scale,
            "shift": coord_shift,
            "error": error * 100
        }

        print("Done ", animal, factor)

    with open('model_description.json', 'w') as fp:
        json.dump(results, fp, indent=4)


main()
```

calculate.py - the python file to run which will then prompt you to input all the parameters and then calculates your total score based on the model_description.json file generated by main.py

```
import functions
import json

# NEEDED FOR RADAR GRAPH
# import plotly.express as px
# import pandas as pd


def main():
    model_data_file = open('model_description.json')
    models_list = json.load(model_data_file)

    animal = input('Input Animal: ').lower()

    if not animal in models_list:
        print(f"Animal {animal} not found.")
        return

    NORMALISED_COORD_WIDTH = 2
    FUNCTION_DICT = {
        "s": functions.s,
        "l": functions.l
    }

    model = models_list[animal]

    animal_mass = float(input("Enter Animal Size (kg): "))
```

```
total_score = 1

chart = {
    "names": [],
    "scores": []
}

for parameter_name, parameter in model.items():
    if parameter_name == 'info':
        continue

    value = float(input(f"Input '{parameter_name}' value: "))

    if parameter_name in model["info"]["weight_impact"]:
        average_weight = model["info"]["average_weight"]
        mass_weighting = model["info"]["weight_impact"][parameter_name]

        value = (1-mass_weighting)*value+mass_weighting*value*average_weight / animal_mass
        print("Adjusted Value: ", value)

    normalised_value = None
    if parameter["shift"] != None and parameter["scale"] != None:
        normalised_value = NORMALISED_COORD_WIDTH * \
            (value - parameter["shift"]) / parameter["scale"]
    else:
        normalised_value = value

    score = FUNCTION_DICT[parameter["function"]
                  ](normalised_value, parameter["a"], parameter["b"])

    print(f"{parameter_name} score: {score}")

    total_score *= score

    chart["names"].append(parameter_name.replace('_', ' ').capitalize())
    chart["scores"].append(score)

print(f"Total Score: {total_score}")

# NEEDED FOR RADAR GRAPH
# df = pd.DataFrame(dict(
# r=chart["scores"],
# theta=chart["names"]))
# fig = px.line_polar(df, r='r', theta='theta', line_close=True)
# fig.show()


main()
```

model_description.json - The file containing all g, h, shift, scale, a, b and error values for each factor for each pet. Used in calculate.py to determine total score.

```
{
   "cat": {
       "info": {
           "average_weight": 4.5,
           "weight_impact": {
               "capability": 0.5,
               "property_size": 1,
               "pet_budget": 0.51
           }
       },
       "capability": {
           "function": "s",
           "a": 0.11259616506565033,
           "b": 0.6479022584174937,
           "scale": 1.0,
           "shift": 0.0,
           "error": 0.001014699321448383
       },
       "pet_budget": {
           "function": "s",
           "a": 0.23897113080984178,
           "b": 1.1169415983388984,
           "scale": 2016.0,
```

```
            "shift": 0.0,
            "error": 0.07608246265589798
        },
        "distance_to_park": {
            "function": "l",
            "a": 1.0050459405082652,
            "b": 0.7943282347,
            "scale": null,
            "shift": null,
            "error": 0.13308618094577426
        },
        "property_size": {
            "function": "s",
            "a": 0.060027656663885764,
            "b": 0.13205657531038,
            "scale": 582.0,
            "shift": 18.0,
            "error": 1.463046392931884e-05
        },
        "time_at_home": {
            "function": "s",
            "a": 0.16310919981958674,
            "b": 0.5637023367602201,
            "scale": 72.0,
            "shift": 0.0,
            "error": 0.9571964732654233
        },
        "criminal_record": {
            "function": "s",
            "a": 0.23100857735150035,
            "b": 1.3163431030659334,
            "scale": -3.0,
            "shift": 3.0,
            "error": 0.46512705285771566
        },
        "time_to_vet": {
            "function": "l",
            "a": 1.0225088263394153,
            "b": 0.5,
            "scale": null,
            "shift": null,
            "error": 0.8758666663661047
        },
        "previous_ownership": {
            "function": "s",
            "a": 0.808662670198398,
            "b": -1.0946849407016277,
            "scale": 3.0,
            "shift": 0.0,
            "error": 0.0012116123442824198
        },
        "time_dedicated": {
            "function": "s",
            "a": 0.3461206457165513,
            "b": 0.47802508437862784,
            "scale": 55.0,
            "shift": 5.0,
            "error": 0.0156797218918216
        }
    },
    "dog": {
        "info": {
            "average_weight": 18.4,
            "weight_impact": {
                "capability": 0.5,
                "property_size": 1,
                "pet_budget": 0.51
            }
        },
        "capability": {
            "function": "s",
            "a": 0.22182732182387455,
            "b": 1.0959854301809502,
            "scale": 1.0,
            "shift": 0.0,
```

```
        "error": 0.03509567208527938
    },
    "pet_budget": {
        "function": "s",
        "a": 0.4995590843388608,
        "b": 0.8044502994329901,
        "scale": 2618.0,
        "shift": 600.0,
        "error": 0.7942163730116324
    },
    "distance_to_park": {
        "function": "l",
        "a": 1.0003200340197846,
        "b": 0.794328347,
        "scale": null,
        "shift": null,
        "error": 0.012012461292428384
    },
    "property_size": {
        "function": "s",
        "a": 0.08011028868467826,
        "b": 0.16471401859417562,
        "scale": 1900.0,
        "shift": 100.0,
        "error": 0.4309495887417838
    },
    "time_at_home": {
        "function": "s",
        "a": 0.15615023363274586,
        "b": 0.8610891102148283,
        "scale": 79.0,
        "shift": 0.0,
        "error": 0.8448351363647556
    },
    "criminal_record": {
        "function": "s",
        "a": 0.23089541408449962,
        "b": 1.3163450092579274,
        "scale": -3.0,
        "shift": 3.0,
        "error": 0.4651253933085098
    },
    "time_to_vet": {
        "function": "l",
        "a": 1.0225078932267164,
        "b": 0.5,
        "scale": null,
        "shift": null,
        "error": 0.8758666743441486
    },
    "previous_ownership": {
        "function": "s",
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        "b": -1.0948250716587886,
        "scale": 3.0,
        "shift": 0.0,
        "error": 0.0012116040062809604
    },
    "time_dedicated": {
        "function": "s",
        "a": 0.4057731976511588,
        "b": 0.5577070794583739,
        "scale": 55.0,
        "shift": 15.0,
        "error": 0.10274832649887493
    }
},
"horse": {
    "info": {
        "average_weight": 550,
        "weight_impact": {
            "capability": 0.5,
            "property_size": 1,
            "pet_budget": 0.51
        }
```

```
    },
    "capability": {
        "function": "s",
        "a": 0.11272913256538115,
        "b": 1.18110327041114,
        "scale": 1.5,
        "shift": 0.0,
        "error": 5.10932264328824e-05
    },
    "pet_budget": {
        "function": "s",
        "a": 0.6091119038545725,
        "b": 0.49298219699638307,
        "scale": 5800.0,
        "shift": 1200.0,
        "error": 0.07940892531407621
    },
    "property_size": {
        "function": "s",
        "a": 0.19438940413464584,
        "b": 0.42716612624404704,
        "scale": 7500.0,
        "shift": 500.0,
        "error": 1.0125084039899277e-05
    },
    "time_at_home": {
        "function": "s",
        "a": 0.15523156249833445,
        "b": 0.5347289708300963,
        "scale": 49.0,
        "shift": 0.0,
        "error": 0.7619512702956786
    },
    "criminal_record": {
        "function": "s",
        "a": 0.23117775336141044,
        "b": 1.316075072155366,
        "scale": -3.0,
        "shift": 3.0,
        "error": 0.46513311777737054
    },
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        "a": 1.0045632350478697,
        "b": 0.4,
        "scale": null,
        "shift": null,
        "error": 0.599343948099073
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    "previous_ownership": {
        "function": "s",
        "a": 0.25300316285963553,
        "b": -0.21952180603255256,
        "scale": 10.0,
        "shift": 0.0,
        "error": 0.026987097410021206
    },
    "time_dedicated": {
        "function": "s",
        "a": 0.1810788865914346,
        "b": 0.6237536071198797,
        "scale": 180.0,
        "shift": 0.0,
        "error": 0.7619772063504613
    }
},
"fish": {
    "info": {
        "average_weight": 0.03,
        "weight_impact": {
            "pet_budget": 0.8
        }
    },
    "capability": {
        "function": "s",
```

```
        "a": 0.16086297576054215,
        "b": 0.9254655744737448,
        "scale": 0.7,
        "shift": 0.0,
        "error": 0.0011684690525027022
    },
    "pet_budget": {
        "function": "s",
        "a": 1.0325158747031975,
        "b": 0.04887833092641694,
        "scale": 64.0,
        "shift": 40.0,
        "error": 0.22344125086669492
    },
    "time_at_home": {
        "function": "s",
        "a": 0.023874129602770508,
        "b": 0.2534505055012491,
        "scale": 49.0,
        "shift": 0.0,
        "error": 0.2500001023724073
    },
    "criminal_record": {
        "function": "s",
        "a": 0.29810626310980537,
        "b": 0.6648401421742232,
        "scale": -3.0,
        "shift": 3.0,
        "error": 0.013681147597349754
    },
    "time_to_vet": {
        "function": "l",
        "a": 1.0178954820945154,
        "b": 0.9,
        "scale": null,
        "shift": null,
        "error": 0.09811747249319087
    },
    "previous_ownership": {
        "function": "s",
        "a": 0.8089407175827075,
        "b": -1.0949602244858854,
        "scale": 30.0,
        "shift": 0.0,
        "error": 0.0012118012888085107
    },
    "time_dedicated": {
        "function": "s",
        "a": 0.4303939423887063,
        "b": -0.6279775821751146,
        "scale": 9.0,
        "shift": 1.0,
        "error": 0.1067208063277114
    }
},
"bird": {
    "info": {
        "average_weight": 0.35,
        "weight_impact": {
            "pet_budget": 0.8
        }
    },
    "capability": {
        "function": "s",
        "a": 0.14085597383287132,
        "b": 0.809624390934693,
        "scale": 0.8,
        "shift": 0.0,
        "error": 0.0010164353635370126
    },
    "pet_budget": {
        "function": "s",
        "a": 0.8486508540782229,
        "b": -0.04208729367875491,
        "scale": 285.0,
```

```
            "shift": 75.0,
            "error": 0.08645762211493158
        },
        "time_at_home": {
            "function": "s",
            "a": 0.1114405342428772,
            "b": 0.42545907088118184,
            "scale": 49.0,
            "shift": 0.0,
            "error": 0.9180812166149512
        },
        "criminal_record": {
            "function": "s",
            "a": 0.23056869232017285,
            "b": 1.3162060534898827,
            "scale": -3.0,
            "shift": 3.0,
            "error": 0.4651346346262895
        },
        "time_to_vet": {
            "function": "l",
            "a": 1.0225083891866902,
            "b": 0.5,
            "scale": null,
            "shift": null,
            "error": 0.8758666674382373
        },
        "previous_ownership": {
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            "a": 0.8088374158487632,
            "b": -1.0948370966622603,
            "scale": 3.0,
            "shift": 0.0,
            "error": 0.0012116796281161002
        },
        "time_dedicated": {
            "function": "s",
            "a": 0.414454277462991,
            "b": -0.19689200033110552,
            "scale": 27.0,
            "shift": 3.0,
            "error": 0.24380460501835277
        }
    }
}
```


Generalisation of Model (Q2)

population_estimates.py - code similar to calculate.py but that first creates a set of households with data representative of the country based on input data in country_info -> COUNTRY.tsv

```
import csv
import json
import functions
import random
import os
# import matplotlib.pyplot as plt


def main(country, animal, animal_mass):
  model_data_file = open('model_description.json')
  models_list = json.load(model_data_file)

  country_info_file = open(os.path.join('country_info', f"{country}.tsv"))
  scaling_info_file = open(os.path.join('country_info', "scaling.tsv"))

  animal_type_scaling = {}
  pet_scaling_list = [None, ]

  for line_num, line in enumerate(scaling_info_file):
```

```
    info_list = line.split('\t')
    for index, info in enumerate(info_list):
        if line_num == 0:
            if index != 0:
                animal_type_scaling[info] = {}
                pet_scaling_list.append(info)
        elif index != 0:
            animal_type_scaling[pet_scaling_list[index]
                                ][info_list[0]] = float(info)

HOUSES_TO_SIMULATE = 100000
SELECTION_VALUE = 0.1
FACTOR_COUNT = 9

house_examples = {}

for line in country_info_file:
    factor_name, mean, sd = line.replace('\n', '').split('\t')
    if mean == 'mean':
        house_examples[factor_name] = []
        for i in range(HOUSES_TO_SIMULATE):
            house_examples[factor_name].append('mean')
        continue

    mean = float(mean)
    sd = float(sd)

    if animal in animal_type_scaling:
        if factor_name in animal_type_scaling[animal]:
            mean *= animal_type_scaling[animal][factor_name]
            sd *= animal_type_scaling[animal][factor_name]

    house_examples[factor_name] = []
    for i in range(HOUSES_TO_SIMULATE):
        house_examples[factor_name].append(random.normalvariate(mean, sd))

if not animal in models_list:
    print(f"Animal {animal} not found.")
    return

NORMALISED_COORD_WIDTH = 2

FUNCTION_DICT = {
    "s": functions.s,
    "l": functions.l
}

total_scores = []

for house_num in range(len(house_examples["criminal_record"])):
    model = models_list[animal]

    total_score = 1
    for parameter_name, parameter in model.items():
        if parameter_name == 'info':
            continue

        value = house_examples[parameter_name][house_num]

        if value == 'mean':
            total_score *= SELECTION_VALUE**(1/FACTOR_COUNT)
        else:
            if parameter_name in model["info"]["weight_impact"]:
                average_weight = model["info"]["average_weight"]
                mass_weighting = model["info"]["weight_impact"][parameter_name]

                value = (1-mass_weighting)*value+mass_weighting * \
                    value*average_weight / animal_mass

            normalised_value = None
            if parameter["shift"] != None and parameter["scale"] != None:
                normalised_value = NORMALISED_COORD_WIDTH * \
                    (value - parameter["shift"]) / parameter["scale"]
            else:
                normalised_value = value

            score = FUNCTION_DICT[parameter["function"]
                                  ](normalised_value, parameter["a"], parameter["b"])

            total_score *= score

    total_scores.append(total_score)

with open(f'data.csv', 'w', newline='') as f:
    writer = csv.writer(f)
```

```
        writer.writerows([total_scores])

    return str((len([x for x in total_scores if x >= 0.1]) / len(total_scores)) * 100) + '%'

    # Display Histogram
    # plt.hist(total_scores, bins=50)
    # plt.gca().set(title='Frequency Histogram', ylabel='Frequency')
    # plt.show()


country = input("Input Country: ").lower()
animal = input("Input Animal: ").lower()
mass = float(input(f"Input {animal} mass: "))

result = main(country, animal, mass)

print("Percentage Passing: ", result)
```

Application of Model (Q3)

For question 3, the population estimate was used but with different input values for different countries, different years and different animals. This was done by modifying the few ending lines of population_estimates.py with:

```
masses = [4.5, 18.4, 0.35, 0.03, 550]

values = []

for year in [2024, 2029, 2034, 2039]:
    values_list = []
    country = 'singapore'
    for index, animal in enumerate(['cat', 'dog', 'bird', 'fish', 'horse']):
        values_list.append(main(f"{country}-{year}", animal, masses[index]))
    values.append(values_list)

    with open('data.csv', 'w', newline='') as f:
        writer = csv.writer(f)
        writer.writerows(values)
```

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9.3.2 Considerations, Assumptions and Justifications

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