1 Introduction

In my own life, one of my favorite hobbies is playing the Tabletop Role-playing Game Dungeons and Dragons (D&D). In the game, players create a player character (PC) that they use to tell a collaborative story with others.

Over the years, I've collected data for thirty-one of the characters that I've created for D&D games, also known as campaigns. I've noticed that the lifespan of these characters, defined by the number of days between the first and last time I play them, tend to vary greatly. Some character last for years of enthusiastic play. Other characters, however, sputter out after a mere couple weeks due to disinterest in the campaign. In most of my cases, the lifespan of the campaign and the character are the same. However, there is the rare case where a PC dies, and I make a new one during the course of the same campaign.

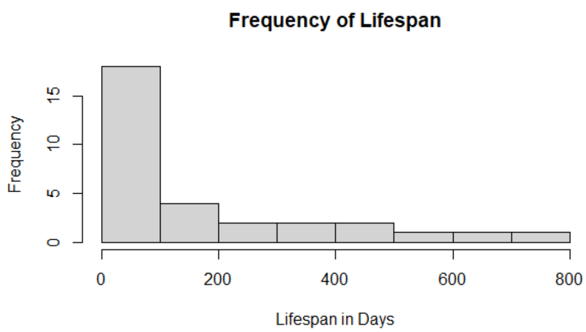
Using techniques learned from this class including censoring, prior selection, and model selection, my goal is to create a Bayesian model from my own data to analyze which factors, both involving the campaign itself and the characters I make, to determine which factors most affect the lifespan of a character. For example, are characters where I play with strangers more likely to have short lifespans due to less accountability in continuing the campaign? Are there certain character traits that I'm subconsciously less enthusiastic about, which would inadvertently shorten the campaign and character's lifespan?

2 Data

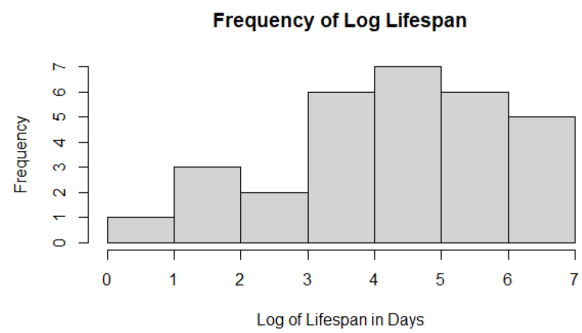
My data consists of 31 characters that I have made from November 2017 until present. There are two files included with the project. `PC Winbugs Data.csv` has the data in a more human-readable format, and it is using in the accompanying R file used for plotting. However, it also includes data not used in Openbugs. The file `PC_Winbugs_Final` includes data formatted to use with Openbugs. The Openbugs data includes the following attributes:

1. **Start.Level**: The integer level at which the character begins at.
2. **Players**: The integer number of players in the campaign that the character is in
3. **Age**: The integer age of a character as represented by their age - 17. (This was done to simplify the probability distribution of age.)
4. **Str**: The integer strength score of the character.
5. **Dex**: The integer dexterity score of the character.
6. **Con**: The integer constitution score of the character.

7. **Int**: The integer intelligence score of the character.
8. **Wis**: The integer wisdom score of the character.
9. **Cha**: The integer charisma score of the character.
10. **Type**: The game medium. This is categorical data.
    (a) **PBP**: The game is run play-by-post, which is a text-based medium similar to collaboratively writing a novel.
    (b) **Live**: The base-case. The game is run either in-person or online via video call. This is similar to improvisational theater.
11. **Gender**: The gender of the character. This is a categorical variable.
    (a) **GenderMan:** The character is a man.
    (b) **GenderNonbinary:** The character is nonbinary.
    (c) **GenderWoman:** The base-case. The character is a woman.
12. **KnowDM**: A boolean variable describing whether I already knew the Dungeon Master (DM) before joining the game using this character. The DM is essentially the leader of the game.
13. **Caster**: How much magic the character can cast. This is a categorical variable.
    (a) **FullCaster**: The character primarily casts magic.
    (b) **HalfCaster**: The character has some magic, but it is not their main focus.
    (c) **NoCaster**: The base-case. The character does not have magic.
14. **Campaign**: A categorical variable focusing on the fate of the campaign.
    (a) **CampaignEnd**: The campaign officially ended, whether the story finished or the DM decided to discontinue it.
    (b) **CampaignRebirth**: The DM decided to restart the campaign.
    (c) **CampaignHiatus**: The DM put the campaign on hiatus. Whether it will continue in the future is unknown.
    (d) **CampaignFizzled**: The game died due to lost interest, but it never received closure.
    (e) **CampaignOther**: This includes cases where the character either died, prompting me to make a new character in the same campaign, or I left the campaign.
    (f) **CampaignOngoing**: The base-case. The campaign is still ongoing, and I am an active player.
15. **Time**: For inactive characters, the number of days in which they were active.
16. **Time.cen**: For active characters, the number of days they have been active *so far*.



(a) A histogram of the time and time.cen



(b) A histogram of the logs of time and time.cen

Figure 1: Histograms of lifespan data

3 Methodology

3.1 Base Model

The base methodology was inspired by the second problem in homework 6, which had a similar premise.

When plotting the general distribution of lifespans, we see that they tend to follow an exponential distribution as seen in Figure 1 below. Most characters do not last very long, while a few last for years. Using a log transformation, the data generally has a much more even spread.

To account for this, we set up the basic regression form as $\log(y) = \beta_1 + \beta_2 * x_1 + ... + \beta_{n+1}x_n$.

We try two approaches for our response of Time. One is modeling the response variable as an exponential distribution, as it is appropriate for a distribution where probability decreases over time and a distribution based on the time until an event happens.

$$\text{Time} \sim \text{Exp}(\lambda) \quad \text{where} \quad \lambda = y$$

The other method is using a normal distribution, as is done in standard linear regression.

$$\text{Time} \sim \text{N}(\mu, \frac{1}{\tau}) \quad \text{where} \quad \mu = y$$

In addition, we will use censoring because some of the characters are still active and being played at present. While their Time response variable is the amount recorded at the time of this analysis, their true lifespans will be determined in the future and larger than the current response variable.

3.2 Model Selection

For this project, we will ultimately choose a model based on the Laud-Ibrahim measure. This code calculation was borrowed from the class file `Hald.odc`. In addition, by using OpenBugs' correlation tool, we will choose a model that avoids strong correlation between coefficients.

For models that do use the normal distribution, we use adjusted R^2 as an accompanying metric as well. This will help diagnose cases of over-fitting. The code to calculate R^2 in Winbugs was borrowed from the class file `fat11.odc`.

Unfortunately, due to there being 22 different predictors, it would be computationally taxing to compare all possible combinations using Openbugs. Instead, we began with a full model and then tried different models based off of previous results. For brevity, the models are condensed to text description, though all can be viewed in detail in their respective .odc files.

1. **Model 1:** A full model that utilizes an exponential distribution.
2. **Model 2:** A full model that utilizes a normal distribution.
3. **Model 3:** A model that uses Strength, Dexterity, Constitution, Intelligence, Wisdom, and Charisma and utilizes an exponential model.
4. **Model 4:** A model that uses Strength, Dexterity, Constitution, Intelligence, Wisdom, and Charisma and utilizes a normal model.
5. **Model 5:** A model that uses Gender and Caster in an exponential model.
6. **Model 6:** A model that uses Gender and Caster in a normal model.
7. **Model 7:** A model that uses start.level, players, time.until.first.battle, TypePBP, KnowDM, CampaignEnd, CampaignRebirth, CampaignHiatus, CampaignFizzled, and CampaignOther in a normal model.
8. **Model 8:** A model that uses Players, Dexterity, Constitution, Charisma, TypePBP, GenderNB, CampaignEnd, CampaignRebirth, CampaignHiatus, CampaignFizzled, and CampaignOther in a normal model.
9. **Model 9:** A model that uses strength, dexterity, constitution, wisdom, and charisma that utilizes a normal model.

3.3 Priors

In this project, there are five groups of priors that were chosen.

3.3.1 Coefficients

For all coefficients, a noninformative normal prior, $N(0, 1000)$, was used. This is because we know the shape of the coefficients should be normal for regression with a mean of zero. However, nothing else is known for the coefficients.

3.3.2 Age

There were several characters who were never assigned ages. To account for the missing data, I used the gamma prior, Gamma(3.5, 0.5), to fill missing gaps. My reasoning was that I know I tend to play characters in their early twenties, as that is near my own age, with a general distribution that is skewed right. This makes the expected value 7, which is 24 when accounting that 17 is added to the data to determine real age.

3.3.3 Stats

One PC was missing her strength, dexterity, constitution, intelligence, wisdom, and charisma scores. To impute for these, I decided to use priors that mimic the dice-rolling method I originally used to create the character. The method is to roll four dice and use the sum of the highest three.

After simulating this in Python in the file `4d6.py`, I simplified the distribution to $N(12.5, 8)$. This includes a slight boost to the mean to account for cases where, when players roll all scores incredibly low, they are often allowed a reroll. This was used for all stats except dexterity.

Dexterity, however, I knew would be approximately in the 16-18 range. This is because the character was originally built to rely on dexterity as a primary stat and, reasonably, it would be around the value of 16-18. Therefore, I used the prior distribution of $N(17, 0.25)$ to reflect this.

3.3.4 Time Until First Battle

D&D has extensive combat rules, and as a result, Because this is an variable based on time until an occurrence, I used an exponential prior, Exp(0.5), to model missing data. This gives an estimate of four days on average between the first game and the first battle, which would

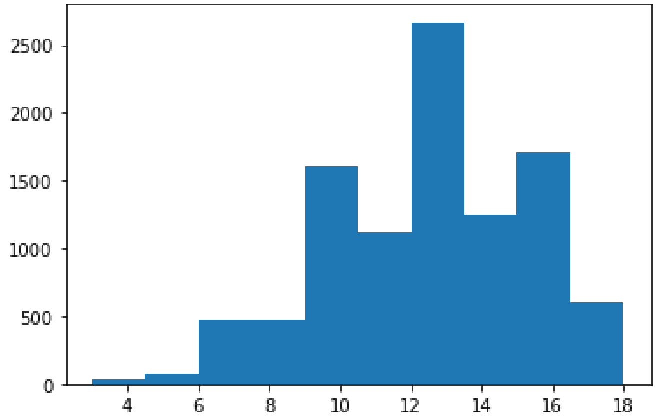


Figure 2: Distribution of stat generation method

be on the lower end of a reasonable assumption. Note that this was determined based on anecdotal experience.

3.3.5 Tau

For regression using the normal distribution, we initialize τ as a Gamma(0.001, 0.001) distribution.

4 Results

	R^2	R^2 adjusted	Laud-Ibrahim Mean
Model 1	NA	NA	4.459E+22
Model 2	0.9991	0.9971	1137.0
Model 3	NA	NA	5256.0
Model 4	0.7679	0.71	1452.0
Model 5	NA	NA	7481.0
Model 6	0.2304	0.1502	1900.0
Model 7	0.9887	0.9832	1773.0
Model 8	0.9972	0.9955	1363.0
Model 9	0.4438	0.3457	1758.0

Table 1: Model Selection Table

In Table 1, we see the results of each model's run, including R^2 values and the Laud-Ibrahim criteria. In Figure 3, we see the correlation between coefficients for each model.

Variable	5%	mean	95%
Players	-0.8695	-0.6147	-0.3709
Dexterity	0.1726	0.3627	0.4471
Constitution	-0.2576	-0.0879	0.06145
Charisma	0.0593	0.1286	0.1725
TypePBP	-1.082	-0.434	-0.01201
GenderNB	0.7386	2.207	2.936
CampaignEnd	-2.325	-2.068	-1.423
CampaignRebirth	-3.047	-2.553	-1.302
CampaignHiatus	-61.8	-14.33	-2.754
CampaignFizzled	-7.265	-5.76	-3.513
CampaignOther	-54.27	-9.179	-1.848

Table 2: Model Selection Table

The discussion in this write-up will provide a summary of findings. For detailed results of coefficients and imputed data, please reference each model's respective OpenBugs file, which has text stats beneath the code. All had a 1000 run burn-in with 1,000,000 updates after.

Using the Laud-Ibrahim crieria, all the normal models performed better than the exponential models. By the criteria alone, Model 2 performed the best. However, due to it being a full model with 22 predictors used on 31 data points, this could very well be a case of overfitting. The adjusted R^2 value supports the notion of overfitting as well, with it being close to 1.

Models 7 and 8, though they have fewer coefficients, still have absurdly high R^2 adjusted values. Model 7 was created by making a model of all external factors (i.e. factors that are about the campaign and not the character), and Model 8 was created by using only factors significant in Model 2 at the 95% confidence level. This may be because each still have over 10 coefficients, which could contribute to overfitting. Model 8, however, doesn't have much correlation between coefficients, which should not contribute to the large R^2.

Model 5, with only 6 coefficients, still has a comparably low Laud-Ibrahim score along with a more reasonable R^2 value. However, it does have correlation between Intelligence and Charisma, as shown in the correlation matrix in Figure 3. However, when intelligence is removed as a predictor, as shown in Model 9, the R^2 adjusted value plummets. While this isn't necessarily a sign that the correlation between intelligence and charisma is inflating R^2 significantly, it points to intelligence being either significant or correlation affecting R^2.

Overall, the best model seems to be Model 8. While it is subject to possible overfitting, with some further trimming down of predictors, it could serve as a good model, especially because there is little correlation between coefficients. The coefficients and their values are provided in Table 2. All coefficients in Model 8 were significant at the 95% confidence level.

The predictors with a negative impact on PC lifespan, while keeping all other predictors constant, are **Players**, **Constitution**, **TypePBP**, **CampaignEnd**, **CampaignHiatus**, **CampaignFizzled**, and **CampaignOther**.

The predictors with a positive impact on PC lifespan, while keeping all other predictors constant, are **Dexterity**, **Charisma**, and **GenderNB**.

The four campaign variables make sense as a negative influence, as they are ways for a campaign to end. Notably, CampaignHiatus has harshest negative effect on lifespan on average. CampaignOther had the second largest, which makes sense as the PC with the lowest lifespan is from a campaign which I left, which falls into this category. CampaignFizzled is third lowest, which makes sense as, anecdotally, campaigns where people lost interest tend to do so early. Finally, CampaignEnd and CampaignRebirth are the least negative.

Additionally, other observations include that live games tend to last longest than those done by PBP, which is a text-based asynchronous medium. This may be influenced by live games having a stronger commitment of people needing to commit to meeting at a certain time rather than simply writing when they can. Games with fewer players are favored over games with more players as well.

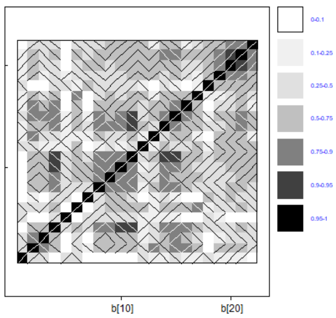
For my own characters, having high dexterity and charisma tends to increase the lifespan of a character. This makes sense, as, anecdotally, I tend to enjoy characters that fight at range, which relies on dexterity, and that have good people-skills, which relies on charisma. These could be factors that subtly influence my own enjoyment of the game, and thus the duration.

Interestingly as well, the heavily imputed variables (Age and Time Until First Battle) had some variation in the models they were used in. However, while Age had some vairbale, Time Until First Battle had less. Neither was significant in Model 2, which may be because they both relied too heavily on a prior with little data otherwise.

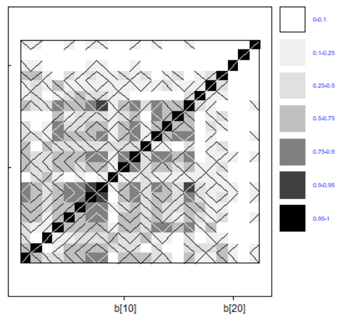
5 Conclusion

While none of the 9 tested models were perfect, Model 8, which took the significant variables from the full normal model, was the best compromise between good prediction and overfitting. Overall, the best model thus far showed a mixture of internal and external factors influencing a PC's lifespan in my own D&D games. Notably, these factors include character stats, the ending of the game, character gender, the number of players, and the format that the game is played through. The heavily imputed variables did not have an impact on the final model.

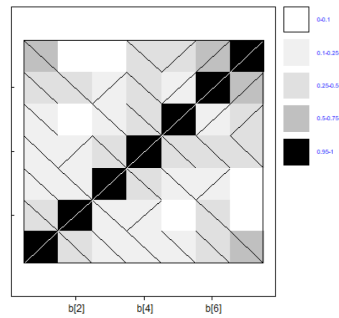
Further tuning of the models could produce a more accurate model that avoids overfitting. In addition, a larger dataset in the future could avoid the pitfalls of overfitting, thus creating a more robust model.



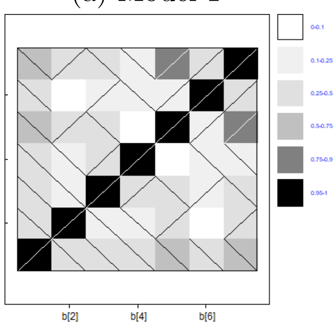
(a) Model 1



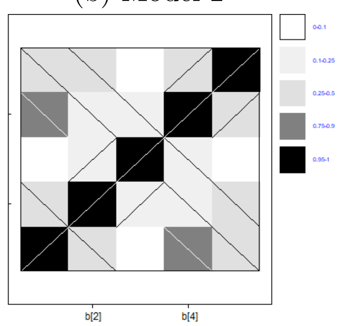
(b) Model 2



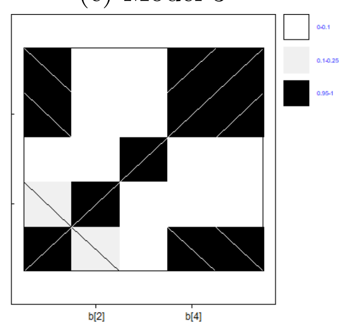
(c) Model 3



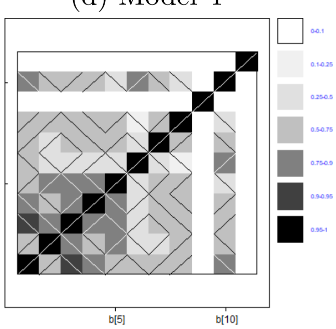
(d) Model 4



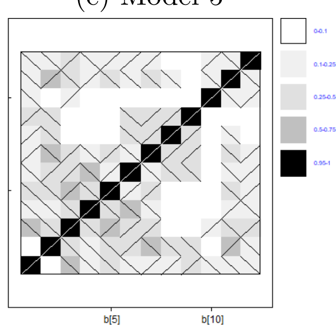
(e) Model 5



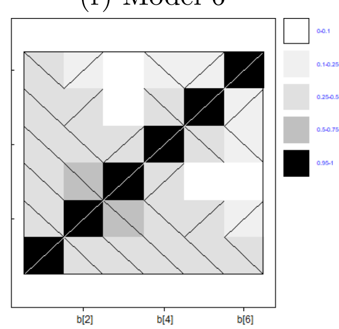
(f) Model 6



(g) Model 7



(h) Model 8



(i) Model 9

Figure 3: Correlation Charts of Model Predictors