MACSS 30100 HW01 Submission

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Building Models

Q1: Deviant aggressive behaviour

Theory 1 posits that deviant aggressive behaviour is learned from experience, based on a reward-punishment calculus that makes it a viable option. It argues that deviant behaviour that persists in society is either rewarded handsomely, or the cost vis-a-vis punishment is much lower than the reward of not being caught. One could also assume that the probability of being caught is low enough that the risk of punishment is sufficiently low. To reduce deviant aggressive behaviour in this framework, social policy could focus on correcting the reward-punishment calculus. Identify measures which decrease the reward derived from the deviant behaviour, or alternatively, increase the punishment to a prohibitively high level. Additionally, measures that increase the likelihood of being caught could also increase the cost of engaging in deviant aggressive behaviour.

The primary contention of Theory 2 is that deviant behaviour is a response to authority and a lack of agency. It argues that frustrations that stem from a lack of power result in deviant aggressive behaviour targeted to authority figures. This deviance serves as a symbolic reassertion of agency. In this framework, any reduction in deviant behviour would have to focus on the individual's feeling of helplessness, and the power structures they're surrounded by. Policymakers could work on programs that reach out to such individuals and help them identify ways in which they can reclaim agency. They could also work on helping them express their frustrations and dissatisfactions in other kinds of behaviour. Additionally, they could work on eliminating the authoritative oppressive figures that are the cause for the feelings of helplessness.

Theory 3 argues that deviant aggressive behaviour is rational as the social rules of the system discriminate and oppress individuals. Deviant individuals recognize that the norms and rules of the system either harm them or do not give them rewards commensurate with compliance or that the rewards are unjustly low for them. Thus, they decide to not conform to the social rules of the system. Reducing deviant aggressive behaviour in this framework could entail a re-balancing of the profit structure for all parties, making it more equitable. This would address the concern of the oppressed groups. Alternatively, social policy could acknowledge that the current system of rules was constructed to preserve a discriminatory hierarchy and that the status quo only serves to perpetuate discrimination. In such a scenario, destroying the social rules of the system and starting afresh would be an option. A more dystopic approach to reduce deviant behaviour would be to impede on the ability of oppressed groups to recognize the injustice they face. Social engineers could create systems which prevent marginalized groups from understanding the cause of their oppression. They could also create myths which strengthen the status quo and thus delegitimize voices that argue for deviant behaviour, making collective deviant action increasingly difficult.

Theory 4 posits an infectious-outbreak model of deviant behaviour – individuals are 'infected' with deviant behaviour after repeated contact with deviant subcultures. These individuals then normalize the deviant behaviour and embrace it, becoming a part of the subculture. In such a model, propensity to engage in deviant behaviour can be addressed in several ways. Policymakers could work on ensuring that the process of making contact with deviant subcultures is prohibitively costly, thus preventing any socialization into these subcultures. Additionally, they could also set up de-radicalization programs that aim to help and convert deviant individuals into law-abiding citizens. Alternatively, policymakers could also actively work on destroying these deviant subcultures.

Q2: Procrastination and its Discontents

Model 1: People are thrill-seekers

Tasks are taken up either under the chore of duty or in a quest of excitement, controlling for everything else. One could argue that people procrastinate less on exciting tasks because they can't wait to do it, experience the thrill of completing something they love doing, and see it to completion. Duties don't provide excitement of any sort, with the only reward being that you have one chore less to complete.

Chores can be made more fun if we add an artificial constraint to it. A race against a clock could certainly be exciting and challenging, adding a component of excitement to a dull task. This could be one explanation for why people procrastinate for certain types of tasks. The looming deadline and the race to completion could plausibly be a source of excitement and adrenaline, making a boring task more fun.

Generalizing this, the time a task is started upon is dependent on the excitement levels of the task.

Model 2: Anxiety drives Procrastination

A plausible alternative explanation for why people often do things at the last minute is that the nature of the task makes them anxious or causes them discomfort. As a result, they try avoiding having to work on that task until it's absolutely unavoidable.

Predictions

Model 1: I would predict that procrastination times would be higher for more boring tasks like chores than intellectually stimulating tasks. Since the model argues that excitement is a key factor in task completion, it follows that boring tasks would be kept low on the list of priorities. Additionally, I would predict that procrastination times for the same task can be brought down with interventions that make the task more exciting (gamification).

Model 2: I would predict that for the same task, people would procrastinate more if latent anxiety levels are higher, owing to other factors or incidents in their lives. A higher latent anxiety level would make an already undesirable chore even more difficult. Additionally, I'd predict that momentum would play a key role in task completion – once a person has begun a fairly onerous task and made some progress, the friction caused by anxiety would dissipate much more quickly.

Selecting & Fitting a Model

Q3: Flexibility-vs-Performance

Flexibility: For this question, I'm defining flexibility as a function of the strength of the assumptions underlying the model. Weaker assumptions about underlying phenomena and the units of measurement translate to a more flexible model.

Performance: I'm defining performance broadly as a combination of accuracy of results, and explainability of the model.

a: When $n >> p$

A flexible model will give you better accuracy in this case, since it has a large amount of data to work off of. The volume of observations will help it examine edge cases more robustly and refine accuracy by fine-tuning the decision boundaries. That said, it's highly possible the reduction in accuracy with a more inflexible model would not be very large, as the number of predictors are low. The latter model – if built off of the right assumptions – needs to capture the variability of a low number of variables, and thus could do just as well as the flexible variant while having greater explainability.

b: When $p >> n$

A flexible model would have much lower accuracy in this case, since it would tend to overfit. The low volume of observations to train on would prevent it from generalizing accurately. Coupled with its lower explainability value, it is the worse option in this case.

c: Non-linear relationship between predictors and response

A flexible model would do better in this case, as it'd be able to better capture the non-linear relationship. The strong assumptions of an inflexible model would lower its accuracy, and any 'explanation' derived would be meaningless.

d: High variance of errors[1]

In the absence of a specified model, I assume we're referring to a sample of data that has a lot of noise. In this case, a flexible model would overfit to capture the noise, missing the true signals/relationships. An inflexible model would be better in this case.

[1] This is a strange case. Errors arise from a model – the errors associated with data alone are measurement errors.

Q4: Bias-Variance trade-offs

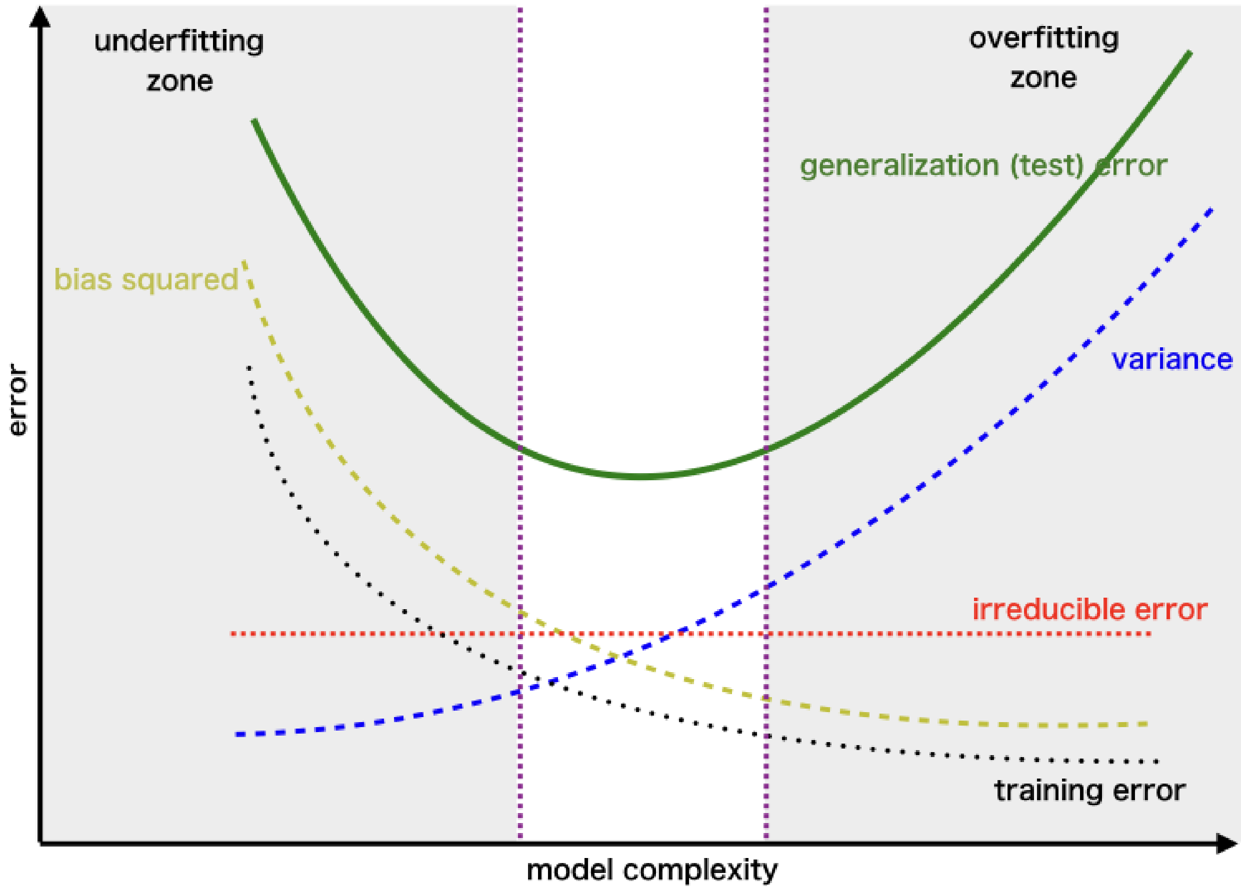

Figure 1: Error Types vs Model Complexity/Flexibility

We know that the expression for expected prediction error, using squared-error loss is:

$$Err(x_0) = \sigma_E^2 + Bias^2(\hat{f}(x_0)) + Var(\hat{f}(x_0)) \tag{1}$$

where:

$$Bias(\hat{f}(x_0)) = E[\hat{f}(x_0)] - f(x_0) \tag{2}$$

$$Var(\hat{f}(x_0)) = (E[\hat{f}(x_0) - E[\hat{f}(x_0)]])^2 \tag{3}$$

σ_E^2 is the *Irreducible Error*; *Bias* is the amount by which the average of the model estimate differs from the true value; *Variance* is the expected squared deviation of the estimate $\hat{f}(x_0)$ around its mean.

1. **Irreducible Error**: As we can see from the graph, Irreducible error has nothing to do with the model itself. It is a construct which indicates that all models we build will have some form of intangible error

(like measurement noise) that cannot be improved upon. It's linear since it has no relationship to the model in any form.

2. **Training Error**: This value decreases with increasing complexity as the model begins to capture greater variability in the training dataset. With sufficiently high complexity, the model begins to mimic the data itself, foregoing the objective of capturing the true data generation process.

3. **Squared Bias**: The bias is a measure that captures deviation from the true value. As model complexity increases and the model begins to mimic the training data more accurately, the bias should decrease.

4. **Variance**: This measure calculates the extent to which the model is sensitive to the choice of training data. As models of higher complexity are extremely specific to the training data, the variance will be quite high since the model may be picking up on noise and missing the true signal.

5. **Test Error**: As we can see in (1), the test error is the sum of the constant Irreducible Error, Squared Bias, and Variance. At low model complexity, its value is driven by the high squared bias, and at high complexity it is driven by the variance. The optimal model complexity zone lies in between these two extremes, where bias and variance are reasonably low.