Outliers and Missing data (Part 2, Missing Data)

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Lecture 05.2.2 (v1.0.1)

Signposting

- Missing Data is an essential topic in **Data Cleaning**.
  - It is about reasoning about what your data are, rather than what you assume them to be.
  - It is how you might detect problems.
- It relates especially to Block 1's EDA lecture, but will be practically essential for every project.
- This is part 1 of Lecture 4.2:
  - Part 1 is about outliers,
  - Part 2 is about missing data.

Intended Learning Outcomes

- ILO1 Be able to **access and process cyber security data** into a format suitable for mathematical reasoning
- ILO2 Be able to **use and apply basic machine learning** tools
- ILO3 Be able to make and report appropriate inferences from the results of applying basic tools to data

Types of missing data

1. **Missing completely at random**.
   - The missing data are completely independent of everything, and can be modelled independently.
   - This sort of missingness is often called **ignorable**.
2. **Missing at random**.
   - The missing data are dependent on observed variables, and can therefore missing status be **modelled independently of the values**.
   - For example, data might be more missing if it is UDP than TCP.
3. **Missing dependent on unobserved parameters**.
   - The missing data are also dependent of latent properties of the model, and therefore must be modelled **at the same time as the values**.
   - For example, data might be more missing if it is from a particular cluster.
4. **Missing dependent on the missing value**.
   - Whether something is missing depends of the value it takes.
   - This is called **censoring** and is a modelling category of its own.

Missingness

- When inferring missingness, it is possible to prove that **it is impossible to detect the type of missingness**.
- This is because more complex forms of missingness can always be constructed…
  - That appear, given the data available, to be from a simpler class of missingness.
- It is therefore always an assumption that you have handled missingness “correctly”.

Methods that discard data

- Discarding data that contain missingness is a common strategy.
  - It can **cause biased inference**, when data are not missing completely at random.
  - It also reduces power.
- We make two main distinctions for how to remove records:
  - **Complete case analysis**: keep all cases that contain no missing data.
  - **Available case analysis**: keep all cases that are complete for each question independently. Therefore different analyses may be differently biased.
- Discarding **variables** (features) due to missingness rate has a similar flavour to available case analysis.
  - Philosophically it can be concerning. “What if I had never measured this feature?” leads to “What if there is some feature I need that I have not measured?”
  - Similar questions arise is sampling. “What if there is an important population that I did not sample?”

Example of available case analysis

```
> summary(lm1)
...
  (188178 observations deleted due to missingness)
```

Methods that impute missing data

- There is only one statistically defendible way to do imputation:

1. Design a **model that you believe** could be true
2. Treat **missing data as parameters** of that model
3. **Test the assumptions** behind the model
4. **Repeat** until the model assumptions cannot be falsified

- In practice this is rarely possible.

Imputation prodedures

- In order of decreasing difficulty of implementation:
- **Bayesian model-based inference**.
  - You may not believe your model, but it is still your best model. Use it for your inference goal.
- **Monte-carlo model-based imputation**.
  - Use your best model, and make multiple random datasets which you then insert into your inference framework.
- **Model-based imputation**.
  - Use your best model, insert the best-guess for all the missing data.
- **Regular imputation**.
  - Use a fast model to impute rapidly.
- Throughout, many biases can be reduced by **retaining and using indicators of missingness status**.

Imputation approaches for large datasets

- Assuming that you can't just run a plausible model, approaches include:
- **Mean imputation**.
  - Replace missing values by the mean.
  - This tends to create many distortions but is often OK when detecting outliers though an appropriate method, e.g. PCA.
- **Regression** or other predictive models.
  - Try to mean-predict the missing values based on what else is present.
- **Nearest neighbour prediction**.
  - Using the mean value of the nearest k-neighbours can work surprisingly well for some problems, though may propagate measurement error.
- **Conservative replacement**.
  - If directions of effects are known apriori, it is sometimes possible to construct a conservative estimate.
  - This requires care and understanding what the variables mean.

Example: Mean imputation

```
## Mean imputation
conndataMmean=conndataM
conndataMmean[is.na(conndataMmean[,"logduration"]),
              "logduration"]=
    mean(na.omit(conndataMmean[,"logduration"]))
tdata=conndataMmean[conndataMmean[,"logduration"]<log(threshold)
lm2=lm(logduration~proto+service +ts +id.resp_p+day,
       data=tdata)
```

Activity 4 of the workshop.

Regression based imputation

- This is a direct extension of mean-imputation.
- We build a model for the covariate,
  - Regression is popular,
  - (though ideally, the model would be robust to missing data itself…)
- And replace the values with the predictions.
- This is conceptually still mean imputation, but where covariates matter.

Nearest neighbour imputation

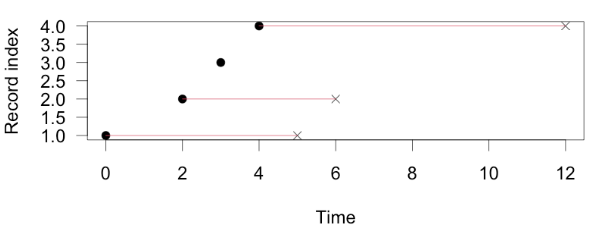
- Define the set of neighbours for each **record** according to a **distance measure**.
- Form a graph with records as nodes in a graph.
- Missing data on a node is **imputed** as the mean/median/etc of its **neighbours**.
- Local graph computations are efficient.

Activity 6 of the Workshop.

Conservative Imputation

- Imputation that is conservative **relative** to some task.
- Usually involves a statistical test…
- In which you can **guarantee** that the test statistic is going to **monotonically decrease** under application of the imputation (assuming that big values are evidence against the null).
- If you can do conservative imputation, and false positives are your target whilst false negatives are not of concern, then conservative imputation is to be recommended.

Example: Conservative testing with censoring



- Is a record B "nested" inside record A?
  - Make "segments" out of each record, i.e. a start and end time.
  - For missing B events, we can impute conservative end times by setting duration to 0.
  - For missing A events, this is not possible.
- **Activity 5** of the Workshop.

Many missing covariates

- When multiple covariates are missing, there is no "trivial" imputation.
- The previous methods can be used with a **iterative scheme**, where an imputation method is used for each in turn.
- **Model-based methods** such as Bayesian models handle missing values as parameters.
  - This can be efficient if missingness is sparse.
- In general, if missingness is dense, there may be multiple possible solution modes.
  - Finding these, and expressing uncertainty, is often a challenge.

Testing imputation procedures

- You should always **test everything**.
- In missing data problems, this means:
  - Taking data that is not missing,
  - Making it missing according to your **best beliefs** (NOT your model!)
  - Applying your missingness model,
  - Seeing how your inference goal is affected by that missingness,
  - Only proceeding if it is not!
- **Activity 7**: checking the imputation models.

Note on special values

- Imputation procedures can only handle special values appropriately if they know about them.
- **Cyber data are full of special values**:
  - 0 is often special: 0 bytes in a packet mean that a data transfer failed; 0 counts of an event may mean that a detector had failed, etc.
  - Often a **zero-inflated** model is needed to handle this: the data are either zero with some probability, or taken from their usual distribution.
- Other values are special.
  - Ports are all special and should often be considered as categorical. There are magic numbers in packet size that give away some protocols.
- **Categorical variables** in general are particularly hard to impute.
  - If you use “best guess” you may change the mean as the most frequent option is artificially even more frequent. Other guesses are worse on average.

Missing data Roundup

- Cyber data are often missing at the data collection stage: the collection procedure is so hopelessly **biased** that additional bias from the treatment of missing data is negligible.
- In this case, ask questions that you believe are **robust** to the data that were available, or are specific to them.
- For example, if you are lucky you may get a good dataset of what your company's network traffic looks like, at a given time, at the perimeter.
  - So ask questions about **changes** to the perimeter over time, not questions about what is going on over the network as a whole.

Reflection

- How do you know what type of missingness are in your data?
- What are the approaches to handling this? What are the challenges?
-
- By the end of the course, you should:
    - Be able to QC your data for missingness,
    - Be able to appraise others' QC attempts,
    - Be able to perform basic imputation.

Signposting

- Next session: Workshop on Missing Data.
- Next block: Moving closer to advanced **machine learning** with Latent Dirichlet Allocation, and the high-level view of the Bayesian methodology that underpins it.
- Further reading:
  - Chapter 9.6 of The Elements of Statistical Learning: Data Mining, Inference, and Prediction (Friedman, Hastie and Tibshirani)
  - Andrew Gelman's Missing Data Notes