Biases, Effects, and Paradoxes

1. Availability Heuristic – Describes that what we think of immediately/first must be more relevant. "If it can be recalled, it must be important". **Example:** Two employees are up for promotion, John and Jane. Jane is considered an overall better candidate than John. In Jane's first year with the company, she accidentally deleted an important company project. Thinking about that incident has you promoting John instead of Jane. This singular memorable event weighed more heavily in this decision than it should have, when you consider the overall track records for both Jane and John.

Sources:

https://www.scribbr.com/research-bias/availability-heuristic/#:~:text=The%20availability%20heuristic%20(or%20availability,is%20most%20available%20to%20us

https://www.verywellmind.com/availability-heuristic-2794824

https://thedecisionlab.com/biases/availability-heuristic

2. Confirmation Bias – People tend to favor information that supports their prior beliefs. Something everyone is likely guilty of at some point in their lives. **Example:** Having a prior belief that left-handed people are more creative than right-handed people. When you see someone left-handed who is an artist, you place more weight on this observation to support what you already believe.

Sources:

https://thedecisionlab.com/biases/confirmation-bias

https://www.verywellmind.com/what-is-a-confirmation-bias-2795024

https://www.simplypsychology.org/confirmation-bias.html

3. Cherry Picking – Making selective choices when presenting evidence in order to emphasize results that support a given position while ignoring findings that are contrary. **Example:** A presidential candidate mentioning all the cities where his tax policy decreased crime rate, while ignoring the cities where the same policy increased crime rate. Politics is a prime example of lots of cherry picking.

Sources:

https://effectiviology.com/cherry-picking/

http://ds-wordpress.haverford.edu/psych2015/projects/chapter/cherry-picking-data/

4. Data Dredging – Also called p-hacking, it involves manipulation and scouring of data in order to find statistically significant results. For example, stopping data collection once a p-value of 0.05 is reached. **Example:** A study of a random sample of people find that Mary and John have the same birthday. You scour through observations and records to try finding evidence of other similarities between them, like maybe they both switched majors in college. You then report that people born on this day are likely to switch majors in college.

Sources:

https://www.scribbr.com/frequently-asked-questions/data-dredging/#:~:text=Data%20dredging%20(also%20called%20p,Excluding%20certain%20participants

https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1124898/

https://sites.warnercnr.colostate.edu/gwhite/wp-content/uploads/sites/73/2017/04/dredging.pdf

5. Survivorship Bias – Concentrating on entities that passed a particular selection criteria while ignoring those that did not pass. In other words, mistaking a visible successful subgroup as the other group. **Example:** There is an infamous example of WWII planes, where the planes came back with bullet holes all over the wings.

When looking at which parts of the plane they needed to reinforce, they realized it was not the wings, as those were the only planes to return from the battlefield.

Sources:

https://thedecisionlab.com/biases/survivorship-bias

https://www.britannica.com/science/survivorship-bias

https://www.scribbr.com/research-bias/survivorship-bias/

13. Simpson's Paradox – A trend that appears in different groups of data but that trend reverses or disappears when the groups are combined or rearranged. **Example:** UC Berkeley was suspected of having a gender bias for admissions. In 1973 their graduate school admitted about 44% of male applicants and only 35% of female applicants. It turned out that women had applied to departments with smaller acceptance rates, and so the marginal values considering all the school's acceptance rate was misguided.

Sources:

https://plato.stanford.edu/entries/paradox-simpson/

https://www.britannica.com/topic/Simpsons-paradox

https://towardsdatascience.com/simpsons-paradox-and-interpreting-data-6a0443516765

14. McNamara Fallacy – Making a decision solely on quantitative observations and nothing else. Named after Robert McNamara and his infamous **example:** during the Vietnam War, he simply looked at the total body count to determine whether the U.S. was in a winning or losing position, as surely higher body count meant the U.S. was winning right? This fallacy disregards meaningful qualitative evidence.

Sources:

https://pubmed.ncbi.nlm.nih.gov/36255018/

https://chacocanyon.com/pointlookout/230222.shtml https://www.formpl.us/blog/the-mcnamara-fallacy-how-researchers-can-detect-and-to-avoid-it

15. Overfitting – We've already talked about this in class, but it's an undesirable machine learning (usually) pattern where we can accurately predict on the training set but not so much on the test set. That is, we have low bias but high variance. Cross validation is a good use for testing for overfitting, as we've seen in the Labs already. **Example:** A machine learning algorithm accurately predicts a college student's academic performance and graduation outcome based on family income, past academic performance, etc. However, the training data only included students from certain ethnic backgrounds. This causes the accuracy of the algorithm to drop for students outside of this data/in the test set.

Sources:

https://aws.amazon.com/what-is/overfitting/#:~:text=Overfitting%20is%20an%20undesirable%20machine,but%20not%20for%20new%20data

https://elitedatascience.com/overfitting-in-machine-learning

https://www.freecodecamp.org/news/what-is-overfitting-machine-learning/

16. Publication Bias – When the outcome of an experiment determines whether someone will publish or distribute the results. For example if you were to publish papers with only statistically significant results and not papers with null results, provided most other factors were the same. **Example:** Pharmaceutical company that concealed information about safety of an antidepressant, by suppressing results that the drug increased risk of suicide in some patients and thus was not effective.

Sources:

https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3341407/

http://ds-wordpress.haverford.edu/psych2015/projects/chapter/publication-bias/#:~:text=Another%20example%20of%20publication%20bias,and%20effectiveness%20of%20an%20antidepressant

https://catalogofbias.org/biases/publication-bias/

17. Dangers of Summary Statistics – We've seen this a lot in class, but remembering Anscombe's Quartet, in which 4 different datasets have the exact same summary statistics, even though charts would tell different stories. It helps to use the more robust statistics like median instead of mean sometimes when dealing with large ranges or outliers. Example: take for example 5 college students, whose ages range from 19, 20, 21, 22, and 1000 (an elf mage who lives a really long time). The mean would show a value of about 216, while the median would be 21. **Another Example:** Oxycontin was marketed as a safe drug because it stayed in a patient's blood over time avoiding symptoms of withdrawal. However, the chart for the study used the y-axis on a logarithmic scale, which made the effect seem not as large.

Sources:

https://www.research.autodesk.com/publications/same-stats-different-graphs/#:~:text=Developed%20by%20F.J.%20Anscombe%20in,the%20datasets%20are%20quire%20similar

https://www.datapine.com/blog/misleading-statistics-and-data/

https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4703239/