SIADS 501 Reading List

December 20, 2019

1 WEEK 1

Status	Reading
Required	Chapter 2, Business Problems and Data
	Science Solutions. In Fawcett, Tom.
	(2013). Data science for business.
	Sebastopol, CA: O'Reilly.
Required	Chapter 1, Interview with Chris Wiggins.
	In Gutierrez, Sebastian. (2014). Data
	Scientists at Work. Berkeley, CA: Apress:
	Imprint: Apress.
Required	Chapter 4, Interview with Erin Shellman.
	In Gutierrez, Sebastian. (2014). Data
	Scientists at Work. Berkeley, CA: Apress:
	Imprint: Apress.
Required	Chapter 16, Interview with Jake Porway.
	In Gutierrez, Sebastian. (2014). Data
	Scientists at Work. Berkeley, CA: Apress:
	Imprint: Apress.
Optional	Chapter 3, Arms Race: Going to College.
	In O'Neil, Cathy. (2016). Weapons of
	Math Destruction: How Big Data
	Increases Inequality and Threatens
	Democracy. New York: Broadway Books.
Optional	Rogati, Monica. (2017). How do I become
	a Data Scientist?. Good Audience blog.
Optional	Kaduk, Taras. (2016). 4 Stages of Data
	Analytics Maturity: Challenging
	Gartner's Model. LinkedIn.

2 WEEK 2

Status	Reading
Required	Pages 19-25 and Chapter 10, The Law of
	Small Numbers (all; pp 109 - 118). In
	Kahneman, Daniel. (2011). Thinking, fast
	and slow. New York: Farrar, Straus and
	Giroux.
Required	Mester, Tomi. (2017). Statistical Bias
	Types explained (with examples) – part 1.
	Data36 blog.
Required	Bailey, Brendan. (2017). Data Cleaning
	101. Towards Data Science blog.
Required	Tait, Andrew. (2017). 10 Rules for
	Creating Reproducible Results in Data
	Science. Dataconomy blog.
Optional	Keng, Brian. (2015). The Gambler's
	Fallacy and the Law of Small Numbers.
	Bounded Rationality blog.
Optional	Lee, N.T., Resnick, P., and Barton, G.
	(2019). Algorithmic bias detection and
	mitigation: Best practices and policies to
	reduce consumer harms. Brookings
	Institution report.
Optional	Data Cleansing. Wikipedia.org

WEEK 3

Status	Reading
Required	Overfitting in Machine Learning: What It
	Is and How to Avoid It.
	EliteDataScience.com
Required	Ray, Sunil. (2018). Improve Your Model
	Performance using Cross Validation (in
	Python and R). Analytics Vidhya. * Read
	Introduction section only.
Required	Ranganathan, P., Pramesh, C. S., & Buyse,
	M. (2016). Common pitfalls in statistical
	analysis: The perils of multiple testing.
	Perspectives in clinical research, 7(2),
	106–107. doi:10.4103/2229-3485.179436
Required	Anderson, Brian. (N.D.)P-Hacking and
	the Problem of Multiple Comparisons.
	Musings, Dr. Brian Anderson's blog.
Required	Spurious Correlations. (N.D.)
	Tylervigen.org.

Status	Reading
Required	Koehrsen, Will. (2018). Correlation
	vs. Causation: An Example. Towards
	Data Science blog.
Required	Wagner, Clifford. (1982). Simpson's
	Paradox in Real Life. The American
	Statistician, 36(1), 46-48.
	doi:10.2307/2684093.
Required	Appleton, D., French, J., & Mark P. J.
	Vanderpump. (1996). Ignoring a
	Covariate: An Example of Simpson's
	Paradox. The American Statistician,
	50(4), 340-341. doi:10.2307/2684931
Required	Rohrer, Julia. (2017). That one weird third
	variable problem nobody ever mentions:
	Conditioning on a collider. The 100% CI
	blog.
Optional (Recommended)	Chapter 5, Desperately Seeking Signal. In
	Silver, Nate. The Signal and the Noise;
	Why so Many Predictions Fail- But Some
	Don't. Penguin Press, 2012.
Optional	Section 3.1, Cross-validation: evaluating
	estimator performance. (N.D.)
	Scikit-learn.org. * Read Section 3.1 only,
	no sub-sections.
	no sub-sections.

4 WEEK 4

Status	Reading
Required	Dykes, Brent. (2016). A History Lesson
	On The Dangers Of Letting Data Speak
	For Itself. Forbes.com.
Required	Zawadzki, Jan. (2018). Storytelling for
-	Data Scientists. Towards Data Science
	blog.
Required	Kaynar-Kabul, Ilknur. (2017).
•	Interpretability is crucial for trusting AI
	and machine learning. The SAS Data
	Science blog.

Status	Reading
Required	Chapter 2, Are You Smarter than a
	Television Pundit? (Required: Start with
	"A Fox-Like Approach to Forecasting"
	and read through "Principle;" rest of
	chapter is optional.). In Silver, Nate. The
	Signal and the Noise; Why so Many
	Predictions Fail– But Some Don't.
	Penguin Press, 2012.
Required	Chapter 6, How to Drown in Three Feet
	of Water. (Required: Read through Figure
	6-2). In Silver, Nate. The Signal and the
	Noise; Why so Many Predictions Fail-
	But Some Don't. Penguin Press, 2012.
Required	Irwin, N., & Quealy, K. (2014, May 02).
	How to avoid being misled by the jobs
	report. New York Times.
Required	Dudek, Tomasz. (2018). But What Is This
	"Machine Learning Engineer" Actually
	Doing? Medium.com.
Required	Newman, Riley. (2015). How We Scaled
	Data Science to all Sides of Airbnb Over 5
	Years of Hypergrowth. VentureBeat.com
Optional	Hypothetical Outcome Plots (HOPs)
	example. Vega Project.
Optional	UW Interactive Data Lab. (2016).
	Hypothetical Outcome Plots:
	Experiencing the Uncertain