LESSON 01

Beyond this week: complementary reading material

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In the list below, we provide some references that could be useful to get beyond this course for exploring topics introduced in week 1.

Applications of Machine Learning

Note: The list below is just a teaser. This topic will be completed on week 2 with a deeper analysis of the opportunities for machine learning to solve business problems.

- **McKinsey's 2016 Analytics Study Defines The Future Of Machine Learning** [link (https://www.forbes.com/sites/louiscolumbus/2016/12/18/mckinseys-2016-analytics-study-defines-the-future-machine-learning/#16d14a7214eb)]

> Five years ago the McKinsey Global Institute (MGI) released Big Data: The Next Frontier For Innovation, Competition, and Productivity, and in the years since McKinsey sees data science adoption and value accelerate, specifically in the areas of machine learning and deep learning. The study underscores how critical integration is for gaining greater value from data and analytics.

- **A Guide to Solving Social Problems with Machine Learning** [link (https://hbr.org/2016/12/a-guide-to-solving-social-problems-with-machine-learning)]

> This mix of enthusiasm and trepidation over the potential social impact of machine learning is not unique to local government or even to government: non-profits and social entrepreneurs share it as well. The enthusiasm is well-placed. For the right type of problem, there are enormous gains to be made from using these tools.

- **Computing, cognition and the future of knowing: How humans and machines are forging a new age of understanding** [link (http://www.research.ibm.com/software/IBMResearch/multimedia/Computing_Cognition_WhitePaper.pdf)]

> Cognitive computing refers to systems that learn at scale, reason with purpose and interact with humans naturally. Rather than being explicitly programmed, they learn and reason from their interactions with us and from their experiences with their environment.

Learning Machine Learning

- **15 hours of expert machine learning videos** [link (http://www.dataschool.io/15-hours-of-expert-machine-learning-videos/)]

> In January 2014, Stanford University professors Trevor Hastie and Rob Tibshirani (authors of the legendary Elements of Statistical Learning textbook) taught an online course based on their newest textbook, An Introduction to Statistical Learning with Applications in R (ISLR).

- **Ten Myths About Machine Learning** [link (https://medium.com/@pedromdd/ten-myths-about-machine-learning-d888b48334a3)]

> Machine learning used to take place behind the scenes: Amazon mined your clicks and purchases for recommendations, Google mined your searches for ad placement, and Facebook mined your social network to choose which posts to show you. But now machine learning is on the front pages of newspapers, and the subject of heated debate. Learning algorithms drive cars, translate speech, and win at Jeopardy! What can and can't they do?

- **A tour of machine learning algorithms** [link (http://machinelearningmastery.com/a-tour-of-machine-learning-algorithms/)]

> In this post, we take a tour of the most popular machine learning algorithms. It is useful to tour the main algorithms in the field to get a feeling of what methods are available. There are so many algorithms available that it can feel overwhelming when algorithm names are thrown around and you are expected to just know what they are and where they fit.

- **10 Algorithms each machine learning engineer should know** [link (http://www.kdnuggets.com/2016/08/10-algorithms-machine-learning-engineers.html)]

> Machine learning algorithms can be divided into 3 broad categories — supervised learning, unsupervised learning, and reinforcement learning. [...] I hope that 10 algorithms on supervised and unsupervised learning will be enough to keep you interested.

- **Minimal and clean examples of machine learning algorithms** [link (https://github.com/rushter/MLAlgorithms)]

> This project is targeting people who want to learn internals of ml algorithms or implement them from scratch. The code is much easier to follow than the optimized libraries and easier to play with. All algorithms are implemented in Python, using numpy, scipy and autograd.

- **25 websites to find datasets for data science projects** [link (https://www.analyticsvidhya.com/blog/2016/11/25-websites-to-find-datasets-for-data-science-projects/)]

> The best way to learn data science is to apply data science. If you are a beginner, you improve tremendously with each new project you undertake. If you are an experienced data science professional, you already know what I am talking about.

- **Seeing Theory, a visual introduction to probability and statistics** [link (http://students.brown.edu/seeing-theory/)]

> Using Mike Bostock's data visualization software, D3.js, Seeing Theory visualizes the fundamental concepts covered in an introductory college statistics or Advanced Placement statistics class. Students are encouraged to use Seeing Theory as an additional resource to their textbook, professor and peers.

- **Inside an AI 'brain' - What does machine learning look like?** [link (https://www.graphcore.ai/blog/what-does-machine-learning-look-like)]

  > A computer that is designed to manipulate graphs is the ideal target for the computational graph models that are created by machine learning frameworks. We've found one of the easiest ways to describe this is to visualize it.

Machine Learning Evaluation

- **How to Evaluate Machine Learning Algorithms** [link (http://machinelearningmastery.com/how-to-evaluate-machine-learning-algorithms/)]

  > In this post you will step through a process to rapidly test algorithms and discover whether or not there is structure in your problem for the algorithms to learn and which algorithms are effective.

- **Metrics to evaluate** [link (http://machinelearningmastery.com/metrics-evaluate-machine-learning-algorithms-python/)]

  > Choice of metrics influences how the performance of machine learning algorithms is measured and compared. They influence how you weight the importance of different characteristics in the results and your ultimate choice of which algorithm to choose.

- **Model evaluation, model selection, and algorithm selection in machine learning** [link (https://sebastianraschka.com/blog/2016/model-evaluation-selection-part1.html)]

  > Fitting a model to our training data is one thing, but how do we know that it generalizes well to unseen data? How do we know that it doesn't simply memorize the data we fed it and fails to make good predictions on future samples, samples that it hasn't seen before? And how do we select a good model in the first place? Maybe a different learning algorithm could be better-suited for the problem at hand?

- **6 testing methods for binary classification** [link (https://www.neuraldesigner.com/blog/methods-binary-classification)]

  > Depending on the type of problem that we are analyzing, there are some specific methods that may help us to study in depth the performance of the predictive model. In this case, we will focus on the following testing analysis methods for binary classification problems

Other sources for Learning BlueMix/Watson

- Cognitive Computing, Question Answering Technologies Behind IBM Watson [link (https://www-304.ibm.com/services/weblectures/dlv/protected/GateProt.wss?handler=Information&action=offering&content=cognitive_computing&customer=watsonwww&offering=wtm1&itemCode=

- Get started with Bluemix with a free online course link (https://www.ibm.com/blogs/bluemix/2016/12/bluemix-essentials-free-online-course/)

- IBM BlueMix Garage link (https://www.ibm.com/cloud-computing/bluemix/garage)

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