Week 2: Neural Networks and Business Processes

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# Neural Networks and Business Processes

The human brain is a supercomputer, with capabilities to reason about situations even when facing ambiguity and imperfect information. In 1949, neural scientists found that the mechanism that accomplishes this feat is a mesh of connected *neurons* (Lukac, Milic, & Nikolic, 2018). Despite unlocking the biological key to producing cognitive learning, the processing power necessary to digitally create these structures was not widely available until the early 2000s. Now cloud technologies, such as Machine Learning as a Service (MLaaS) and Hardware Acceleration as a Service (AaaS), enable ubiquitous access to these data structures for enhancing decision processes. While most organizations understand the value proposition of leveraging technologies like MLaaS, it can be challenging to get started (Garbuio & Lin, 2019). These barriers to entry come with questions around (1) what scenarios are most applicable, (2) how these systems work, and (3) what are some considerations along the way.

## Application to Business Problems

A traditional software program combines *data* and *rules* to produce *outputs*. In contrast, machine learning software takes *data* and *outputs* to derive *rules*. This derivation comes from four major strategies: association rule mining, regression modeling, classification techniques, and clustering techniques (Barua & Mondal, 2019). Many business challenges fit into these categories, such as supply chain management (SCM). SCM systems need to forecast inventory levels through regression analysis. Next, it must classify vendors and choose the right levels to source from each one. As the inventory arrives at various outlets, their performance metrics enable systematic administration by reviewing cluster associations. Finally, when customers purchase a pair of pants, association rules can suggest a matching shirt. Countless additional business scenarios exist with fuzzy rules or general uncertainty.

## Evolution of the problem

Numerous organizations begin their journey into intelligent systems with statistical modeling and variance analysis. These approaches work for many linear models but tend to break down for non-parametric functions (Waal & Toit, 2011). For example, a business wants to appraise houses given a collection of features about the home. Houses come in all shapes and sizes, and this makes it challenging to compare those features directly. Instead, the appraiser must approximate a function that considers these characteristics and their weighted importance. Meanwhile, another company needs to classify handwritten digits, which requires mapping a 32x32 pixel image as its numeric value. Both scenarios and countless more require a mechanism to translate these non-parametric functions into parametric approximations.

## Nature’s solution

In biology, animal brains accomplish these tasks through meshes of neurons that transmit signals across connected synaptic (transforming) and activation (filtering) links (Keller, Liu, & Fogel, 2016). Later, that animal sees an object, and its brain encodes the image into a feature map. These features traverse the neural network and output a collection of responses, such as its food and ten feet away. Over time, the creature *learns* if those responses are correct and revise network weights to encourage or avoid similar situations. Data scientists and mathematicians replicate these ideas by calibrating edge weights, called backpropagation, on connected graphs called neural networks.

## Network Structure

A neural network consists of three building blocks called the input, hidden, and output layers. For instance, an animal image classification system might assign 64x64 pixel images into ten predetermined categories. This example requires an input layer with 4096 neurons, an output layer of ten neurons, and some hidden layers in the middle. Adding more hidden layers enables extracting more details from the image like object edges (layer-1), ears (layer-2), cat’s ears (layer-3), to a tiger’s ears (layer-4) (Fridman, 2017). While more complex networks can extract more insights, it comes with a cost of needing exponentially more data.

Depending on the connectivity configuration, this can become too expensive and require model compression strategies (Cheng, Wang, Zhou, & Zhang, 2018). For instance, the input layer can feed into a series of pooling transforms that downgrade the resolution by averaging every 2x2 pixels. Another strategy might focus on connecting and evaluating local segments of neurons before outputting into global join constructs for prediction (see Figure 1). Meanwhile, other situations like the housing model perform better fully connected to a shallow pipeline. While standard architectures exist for many problem areas, some experimentation is necessary.

Figure 1: Network Structure

