Deep Learning: The Start Of An AI Revolution For Customer Insights Professionals

Continuous Improvement: The Customer Analytics Playbook

by Brandon Purcell, Mike Gualtieri, and Diego Lo Giudice
September 6, 2018

Why Read This Report

Deep learning is the start of a revolution. A revolution because it allows enterprises to create predictive models with uncanny accuracy on image, voice, and natural language data that was previously impossible to analyze. A revolution because the internet giants have all embraced it as a core part of their go-forward AI strategy. And, finally, a revolution because it has only just begun, but over the next three to five years it will disrupt customer insights (CI) pros in their mission to understand their customers.

This is an update of a previously published report; Forrester reviews and updates it periodically for continued relevance and accuracy.

Key Takeaways

Yes, Deep Learning Warrants All The Fuss
Deep learning, a branch of machine learning, focuses on leveraging artificial neural networks to extract features from data for prediction and classification.

Shed Light On Your Darkest Data
Deep learning is particularly adept at dealing with unstructured data, making it ideal for image, video, speech, and text analytics. However, deep learning works on structured data too.

AI Infrastructure Is Required
The vector computations required to train deep learning models are orders of magnitude greater than for classic machine learning. Enterprises wishing to use deep learning must acquire new hardware or use specialized cloud instances, such as graphics processing units (GPUs).

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by Brandon Purcell, Mike Gualtieri, and Diego Lo Giudice
with Srividya Sridharan, Emily Miller, and Jeremy Vale

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Forrester Research, Inc., 60 Acorn Park Drive, Cambridge, MA 02140 USA
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Deep Learning Is The Start Of An AI Revolution

Let's be clear. Despite all the talk about deep learning, we are not on the precipice of pure artificial intelligence that can mimic substantial aspects of human intelligence.[1] Rather, deep learning is about pragmatic AI that CI pros can use to better understand customers: technologies like facial and image recognition, natural language understanding, and voice recognition. The key difference between human intelligence and deep learning is that gray matter is not easily scalable — deep learning models, on the other hand, are scalable, because they are embedded in software that can be replicated digitally in perpetuity.

Deep Learning Is A Branch Of Machine Learning

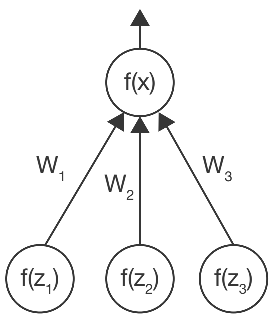
Machine learning is a field of computer science focused on enabling computers to learn from historical data. There isn't one singular, monolithic approach to machine learning. Dozens of specialized categories of machine learning algorithms lend themselves well to specific use cases. One such category has come into its own — artificial neural networks. Neural networks were first conceived in the 1950s, but in 2012 Alex Krizhevsky and his team at the University of Toronto used convolutional neural networks to classify images in the ImageNet competition.[2] This application leveraged multiple "hidden" layers in the neural network, so scientists described them as "deep" (see Figure 1). Thus, deep learning was born. Forrester defines deep learning as:

> *A rapidly evolving machine learning technique used to build, train, and test neural networks that probabilistically predict outcomes and/or classify unstructured data.*

FIGURE 1 How Deep Learning Works

1-1 Neural networks

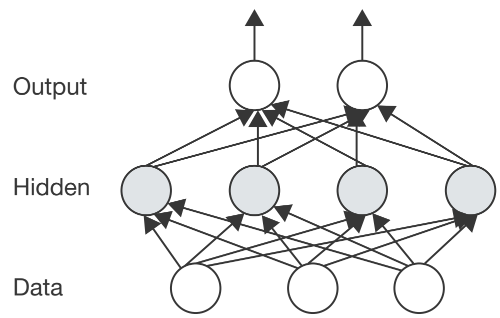
A neuron



$x = w_1 f(z_1) + w_2 f(z_2) + w_3 f(z_3)$

x is called the total input to the neuron, and f(x) is its output

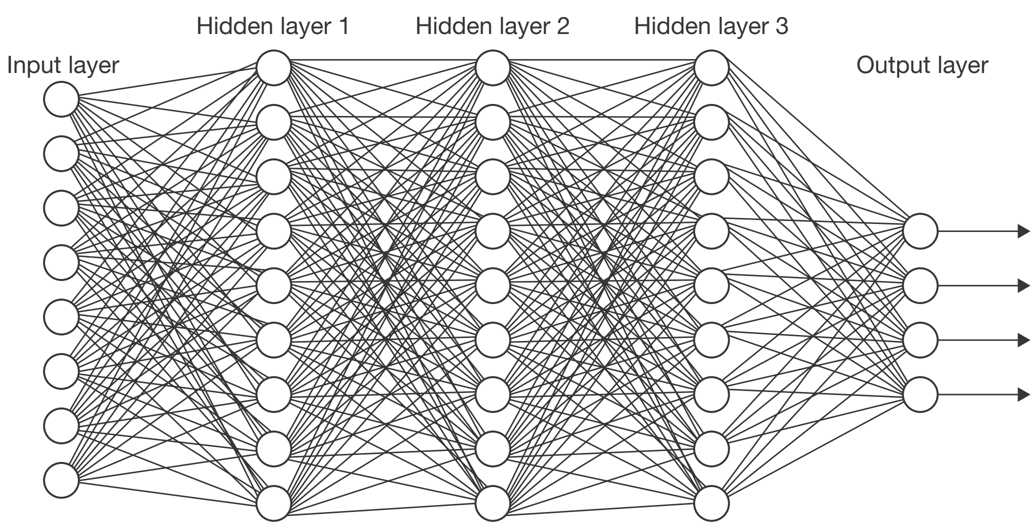
A neural network



A neural network computes a differentiable function of its input. For example, ours computes: p(label | an input image)

Source: Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton, “ImageNet Classification with Deep Convolutional Neural Networks,” NIPS Proceedings, 2012

1-2 A deep learning neural network



Source: Michael A. Nielsen, *Neural Networks and Deep Learning*, Determination Press, 2015

Five Factors Make Deep Learning Different

Forrester clients often ask about the relationship between deep learning and machine learning. At the highest conceptual level, deep learning is no different from supervised machine learning.[3] Data scientists start with a labeled data set to train a model using an algorithm and, hopefully, end up with a model that is accurate enough at predicting the labels of new data that is run through the model. For example, CI pros can use Caffe, a popular deep learning framework, to train a model using thousands or millions of labeled images.[4] Once they train the model, CI pros can use it to probabilistically identify objects in a new image (see Figure 2).[5] Conceptually like machine learning, yes, but deep learning is different because:

› **Gnarly data is welcome.** Deep learning is unique in that it can work directly on unstructured data types such as images, video, and audio. Traditional machine learning must preprocess this data in some way, and the data scientist has to tell the algorithm what to look for that will be relevant to make a decision. Deep learning algorithms do this themselves, without having to be manually programmed. This opens a new world of solving a new class of complex problems that previously relied on preprocessed abstractions of images, voice, video, and non-uniform data. For example, deep learning algorithms can work directly on pixel data — no preprocessing required.

› **Feature engineering is built-in.** One of the biggest challenges with traditional machine learning algorithms is feature engineering. In this process, data scientists hypothesize what data the machine learning algorithm will find useful. This places an iterative burden on data scientists because they often need to introduce new data, new formats of data, or derived data to get the algorithm to work. Deep learning tries to circumvent these challenges with automatic feature extraction. Deep learning models are capable of learning to focus on the right features by themselves, requiring less data preparation from a data scientist. This makes deep learning an extremely powerful tool for modern machine learning.

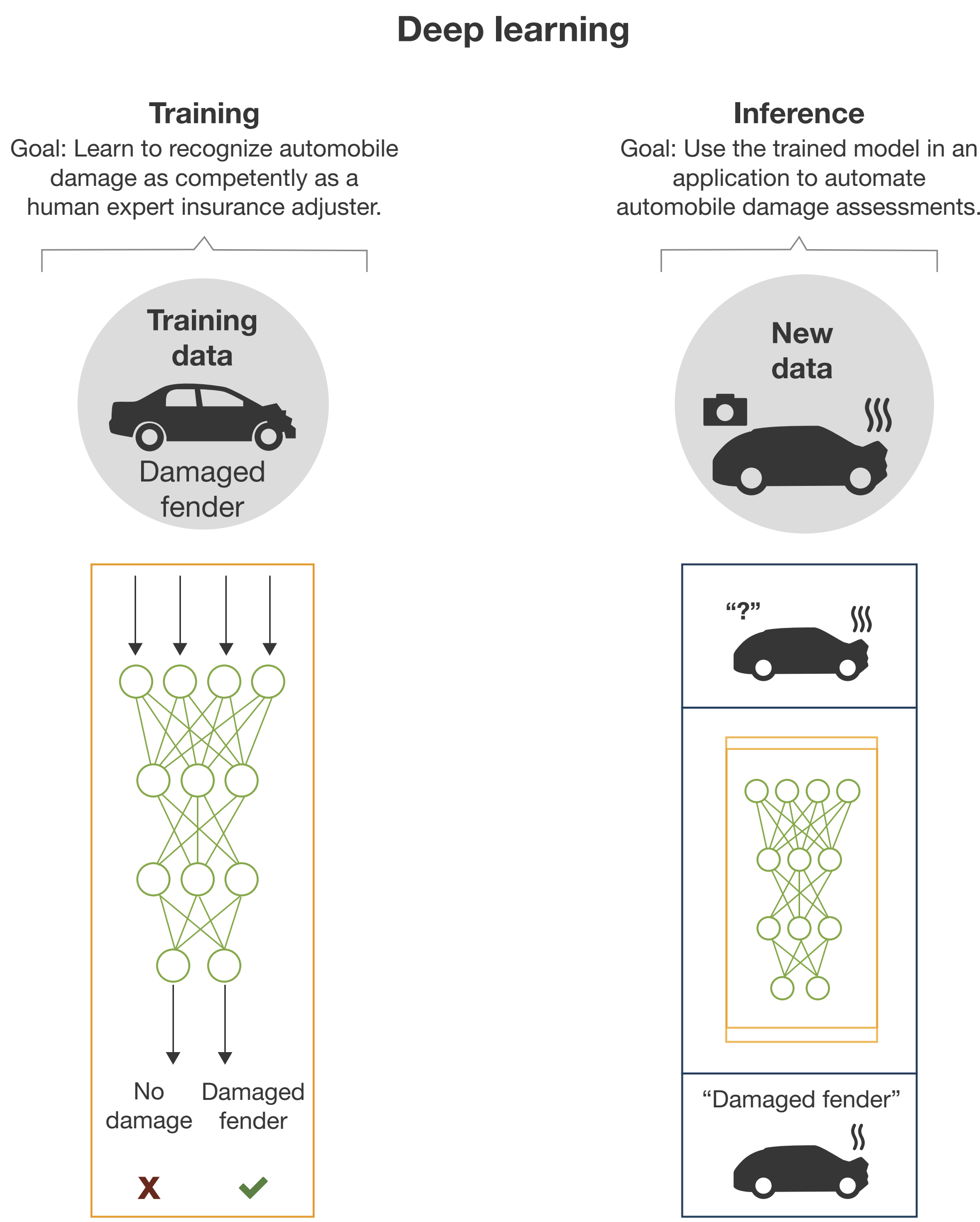
› **A topology design process is a prerequisite.** It's true that deep learning gives data scientists a break when it comes to feature engineering. However, deep learning adds a new task to the process by requiring data scientists to choose from among many permutations of configuration parameters, such as the number of layers in the network or the activation function. Like feature engineering, this can be a very iterative process, with data scientists trying many different combinations until they get it right. Instead of running one combination, testing it, changing the parameters, and trying again, many data scientists take a brute-force approach to designing the network topology by using very large computing clusters to run many combinations simultaneously.[6]

› **Supercomputers are required.** A unique characteristic of deep learning is that the training process involves mathematical vector operations that often result in the need for billions of computations. To meet the need for affordable supercomputer power, deep learning researchers adopted GPUs because they have thousands of cores and can perform the operations necessary to train deep learning networks. NVIDIA is the best-known GPU maker that designs, develops, and markets deep learning GPU systems that support popular, open source, deep learning libraries.

These are supercomputers, but they are affordable to enterprises. Startups like Graphcore and Wave Computing are working on new architectures to speed up deep learning as well. Public cloud players such as Amazon Web Services (AWS) and Google also offer GPU instances that support deep learning. Microsoft with Azure promises fast and flexible FPGA chips for AI.[7]

› **Purpose-built open source libraries are available.** Deep learning has its own set of libraries that are evolving quickly. Many types of deep learning algorithms have been developed. The most popular are multilayered convolutional networks with back propagation, ideal at image and voice recognition, and recurrent neural networks ideal for natural language processing (NLP). Open source options for deep learning are TensorFlow, which is based on reinforcement learning led by Google; ConvNetJS, a JavaScript implementation of neural networks and their common modules, and which includes numerous browser-based examples; Caffe, a deep learning library with many pretrained computer vision models; and Deeplearning4j, an industrial-strength deep learning framework for Java and Scala.[8]

FIGURE 2 Customer Insights Pros Can Use Deep Learning To Identify New Patterns



Source: Adapted graphic from NVIDIA

Revolutions Have Risks — Deep Learning Is No Exception

While deep learning is undeniably powerful and transformative, like any machine learning technique it has its limitations. CI pros who wish to experiment with deep learning should know that deep neural networks:

› **Won't solve your data issues.** Many organizations struggle to access data from multiple sources and ensure quality across them.[9] Deep learning is not a panacea that will solve these data issues — if anything, it will make the need for proper data management even more palpable. For example, training a deep neural network for facial recognition requires not only facial image data but also structured data about the person in the image. If these two data types are not integrated, it will be impossible to develop a facial recognition model.

› **Are inherently opaque.** If your use case requires transparency, deep learning is not the right method to employ because there is no way to explain exactly how the logic of the model works. The numerous layers of the network and millions of weighted connections between nodes make model explanation an area of research but not a reality for commercial use. In situations where regulators require the justification of a model's decision, such as determining a customer's credit-worthiness, you'd be better off using transparent methods like regression analysis . . . for now.[10]

› **Demand large, well-annotated training data sets.** Like all supervised machine learning algorithms, deep neural networks require training data, which is the labeled set of data that teaches a machine learning algorithm how to perform its function. Deep neural networks have particularly voracious appetites for training data. For example, the team of Microsoft researchers who won the ImageNet Large Scale Visual Recognition Challenge in 2015, beating humans at classifying images for the first time in history, used 1.2 million images to train their deep neural networks.[11]

› **Require a hardware budget.** Training deep neural networks requires massive computing horsepower and therefore a significant investment in new hardware. GPUs don't come cheap — NVIDIA's top-of-the-line DGX-1 system for deep learning, which delivers 1,000 teraflops of computing power, has a list price of $149,000.[12] Despite the initial sticker shock, the cost of replicating this horsepower with commodity CPUs would be exceedingly expensive. Some CI pros may choose to avoid steep hardware costs by accessing GPUs on the cloud. AWS, Google, IBM, Microsoft, and NVIDIA all offer access to GPUs on their cloud platforms.

› **Demand scarce, but obtainable skill.** If data scientists are unicorns, then the deep learning expert is their even rarer mythical winged cousin Pegasus. Building models using deep neural networks requires selecting the right type of network for the use case, setting hyperparameters, and having an in-depth understanding of the fundamentals of deep learning. However, as deep learning becomes more popular, the number of people who understand it increases. Google has even launched a service called AutoML that allows nonexperts to build deep learning models for image analysis simply by providing labeled data.

Enterprise Use Cases Boldly Go Where Traditional ML Doesn't

CI pros charged with understanding customers based on the massive amount of structured and unstructured data accruing in real time can benefit greatly from deep learning. In most cases, there's no need to start from scratch — deep learning comes embedded in the voice, image, and NLP cloud services that vendors provide. There are many use cases to start with, and you don't have to be an expert to leverage many of these capabilities. Whether you're in retail, manufacturing, finance, healthcare, government, or any other vertical market in B2C or B2B, here are three proven use cases and the options you have for implementing and using solutions based on deep learning:

› **Speech analytics.** Deep learning has improved the accuracy of speech-to-text transcription; made it easier to extract intent, topics, entities, and relationships; and made it easier to measure the tone, sentiment, and emotion of speakers. Once used mostly to ensure conformity in contact centers, AI-fueled speech analytics now drives engaging customer conversations, gauges customer sentiment, surfaces unexpected customer insights, increases marketing effectiveness, and improves sales conversations.

  Where to get help: Every speech analytics vendor has started incorporating deep learning. However, most vendors are still figuring out how best to leverage AI beyond transcription, and the degree to which vendors leverage AI varies dramatically. CI pros looking to leverage speech analytics can access capabilities via APIs from AWS, Google, IBM Watson, and Microsoft Azure.[13] Many call center and text analytics vendors such as CallMiner, Clarabridge, NICE, and Verint have also incorporated speech analytics into their platforms.[14]

› **Text analytics.** Deep learning presents a real opportunity to improve upon traditional text analytics solutions, which has historically relied heavily on keyword analysis. Last year, only 33% of CI pros reported analyzing their unstructured customer feedback data for insights.[15] This is unfortunate, because this rich data source offers a view into customers' perceptions, intents, and feelings. Additionally, CI pros may use the structured output of text analytics as input into other models, to more accurately predict churn, for example. Some CI pros even use text analytics to develop chatbots for customer service and conversational commerce.

  Where to get help: In the past year, many text analytics vendors such as Clarabridge, IBM, and SAS have begun incorporating deep learning into their platforms to complement their rules-based approach. A few other vendors have developed deep learning alternatives for text analytics as well. Cortical.io leverages Numenta's hierarchical temporal memory model for unsupervised text analysis, and Gamalon developed an algorithm called Bayesian Program Synthesis (BPS) to power its NLP engine.

› **Computer vision.** A picture is worth a thousand words? With deep learning algorithms, that's an understatement. They have enhanced image recognition with very high accuracy, in many cases better than what humans can do. It's possible to use deep learning algorithms to classify and interpret new images, different from ones used during model training, and to identify objects within the images, understand the image itself, write captions, and match with what the algorithm knows about images and figure out similarities in real time. For example, you could analyze image data from social media to understand a customer's lifestyle and enrich your segmentation models. Emotion recognition, a subcategory of image analysis, may eventually allow CI pros to detect and alleviate customer frustration in stores.

Where to get help: Many social media monitoring companies, such as Crimson Hexagon and Talkwalker, now offer image analysis as part of their solutions. And Affectiva is the current leader in emotion recognition. Technically savvy CI pros who are sitting on a corpus of their own image data can use pretrained models exposed as APIs from AWS, Google, IBM, Microsoft, and Salesforce. For more domain-specific applications, CI pros will have to train their own models. Google AutoML and Lobe.ai aim to make computer vision customization easy for business users with an intuitive drag-and-drop interface.

Easy, Intermediate, Or Expert: Three Ways To Get Started

Enterprises don't need to develop their own deep learning algorithms, because these are available for free in open source frameworks or, increasingly, within commercial machine learning solutions.[16] Instead, the opportunity lies in identifying business problems that map well to deep learning use cases, having good data (and a lot of it), and applying the right strategy to build the model, train it, and test it. When building a model using deep learning, CI pros have three main options:

› **Easy: Leverage pretrained models.** The easiest way to get started is to use models that have already been trained. You can either rely fully on pretrained models or improve them with your own data through a process called transfer learning. Transfer learning is one of the key benefits of deep learning because it enables you to build upon existing models instead of starting from scratch. This obviates the need for massive amounts of training data. Pretrained models are available for image, speech, and text analytics. For example, CI pros interested in image recognition can use APIs from Caffe, Clarifai, Google, IBM, Salesforce, and other vendors that have already trained models on huge corpuses of image data.

› **Intermediate: Adopt a low-code approach.** To democratize the use of deep learning, some vendors have developed low-code platforms.[17] Bonsai, recently acquired by Microsoft, offers a simplified platform to make deep learning and other machine learning algorithms accessible to data scientists with basic coding skills. Other companies have embedded deep learning in more traditional machine learning solutions.[18] H2O.ai embeds Google's open source TensorFlow in its product, and SAS offers its own deep learning algorithms in its platform.

› **Expert: Build a model from scratch.** Companies with very specific data and use cases may prefer to train a deep neural network from scratch. In this case, companies will leverage their data scientists and "bring their own data" to a vendor's deep learning platform, which essentially is a library of neural networks. Unlike pretrained models, these algorithms have not seen any data, and they are therefore a tabula rasa, with no preconceived notions of the world. Developers can download open source libraries, such as Caffe, MXNet, and TensorFlow, or use libraries that are integrated into vendors' machine learning solutions.

Recommendations

Teach Your Apps To See, Hear, And Understand

The Who's Tommy didn't need deep learning, but enterprises do. Deep learning can infuse applications with a humanlike ability to sense the world around them. Whether you are trying to assess a customer's emotional state, gauge intent during a phone conversation, or read through thousands of pages of tax code, deep learning will constitute the central nervous system. As CI pros decide whether and where to leverage deep learning, they should ask themselves:

› **Where do I have an abundance of image, audio, and/or text data?** Today's primary applications of deep learning center on unstructured data sources such as image, audio, and text. Many organizations are sitting on a wealth of untapped data in the form of call center recordings and customer emails that contain valuable insights into the customer experience. eCommerce sites have a load of product image data that is ripe for classification and analysis. Other companies may not have access to a large corpus of unstructured data, in which case now is probably not the time for a foray into deep learning. Remember, artificial neural networks are data hungry — starving them could prove costly and futile!

› **Does it make sense to sit on the sidelines (probably not)?** You can always wait for your competitors to front the cost of training initial applications and learn from their mistakes. If they're successful, you can probably catch up if you can recognize the disruption as it happens. In some cases, you may even be able to leverage models trained on their data, because smart AI vendors will look to productize models created and refined for early adopters. For example, Salesforce showcased an Einstein Vision capability that can count the number of Coke products left in a cooler to facilitate the reordering process. While Salesforce developed this capability for Coca-Cola, it's currently available to all Salesforce clients tasked with inventory optimization.

› **Should I lead this revolution (maybe)?** Of course, there is always an opportunity for first-mover advantage. In the deep learning revolution, the barrier to entry is training data. Companies that are able to amass the necessary amount of labeled data to teach a deep neural network to perform its narrow function will certainly have a jump on the competition. And as their applications inevitably get better over time, the distance between these leaders and the rest of the pack may become insurmountable. For example, by leveraging immense numbers of real-time events and data worldwide, who will become the first to outperform in market trading?

What It Means

Garbage In = Garbage Out

Deep learning appears to be magic. Trained models seem to work when tested, but researchers are still trying to figure out exactly why so they can reassure executives or regulators who want to make sure deep learning models don't wreak havoc, say, when embedded in a self-driving car. It's all about the data. It always has been. Deep learning models will only be as good as the training data and especially the granularity of how that training data is labeled. One auto manufacturer includes an image recognition model that can automatically adjust the speed of a car when it "sees" a speed limit sign. Well, a car using that technology saw a sticker on a truck that said the truck would not exceed a certain speed. The car complied with what it thought was a speed limit sign even though that car was driving on the autobahn. Garbage in, garbage out. It's not really a deep learning problem. It's a data problem. Never forget. Garbage in = garbage out. Your models will thank you. Your data scientists will thank you. And your enterprise will thank you.

Supplemental Material

Companies And Organizations Interviewed For This Report

We would like to thank the individuals from the following companies who generously gave their time during the research for this report.

Cray

Enlitic

Google

Gridspace

Horus Technology

Intuition Machine

Salesforce

University of Massachusetts Amherst

Xevo

Endnotes

[1] Forrester offers two definitions for artificial intelligence: pure AI and pragmatic AI. See the Forrester report "Artificial Intelligence: What's Possible For Enterprises In 2017."

[2] Source: Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," NIPS Proceedings, 2012 (http://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf).

[3] See the Forrester report "A Machine Learning Primer For BT Professionals."

[4] To label an image is to associate text with that image. For example, if one has a digital image of a beach scene that includes two people, a dog, a beach ball, and a cooler. A person could label that image with the following text: "people," "dog," "ball," "beach ball," "box," "cooler," "water," "sand," etc.

[5] Many computer vision researchers were brought to metaphorical tears when deep learning beat more traditional approaches for facial recognition. Sad tears because thousands of peer-reviewed papers on computer vision were rendered antiquated. Happy tears because a technology was now showing so much promised without the need for digital models and preprocessing of data.

[6] Source: Forrester interview with UMass researcher about use of $2.5 million hardware grant for computer vision research using deep learning.

[7] FPGA: field-programmable gate array.

[8] Source: Matthew Mayo, "Top 10 Deep Learning Projects on GitHub," KDnuggets, January 13, 2016 (http://www.kdnuggets.com/2016/01/top-10-deep-learning-github.html).

[9] See the Forrester report "The State Of Customer Analytics 2017."

[10] Equifax has discovered a way to make deep neural networks interpretable for the purpose of credit scoring. Source: Gil Press, "Equifax And SAS Leverage AI And Deep Learning To Improve Consumer Access To Credit," Forbes, February 20, 2017 (https://cdn.ampproject.org/c/s/www.forbes.com/sites/gilpress/2017/02/20/equifax-and-sas-leverage-ai-and-deep-learning-to-improve-consumer-access-to-credit/amp/).

[11] Source: Richard Eckel, “Microsoft Researchers’ Algorithm Sets ImageNet Challenge Milestone,” Microsoft Research Blog, February 10, 2015 (https://www.microsoft.com/en-us/research/blog/microsoft-researchers-algorithm-sets-imagenet-challenge-milestone/).

[12] Source: Brian Caulfield, “Blood, Software and 120 Billion Transistors: How NVIDIA Built DGX-1,” NVIDIA blog, July 11, 2016 (https://blogs.nvidia.com/blog/2016/07/11/how-nvidia-built-dgx-1/).

[13] See the Forrester report “AI APIs In The Cloud Are Here.”

[14] See the Forrester report “The Forrester New Wave™: AI-Fueled Speech Analytics Solutions, Q2 2018.”

[15] Source: Forrester/Burtch Works Q2 2017 Global State Of Customer Analytics Online Survey.

[16] See the Forrester report “The Forrester Wave™: Notebook-Based Predictive Analytics And Machine Learning Solutions, Q3 2018” and see the Forrester report “The Forrester Wave™: Multimodal Predictive Analytics And Machine Learning Solutions, Q3 2018.”

[17] See the Forrester report “Use A Light Touch To Govern Low-Code Development Platforms.”

[18] See the Forrester report “The Forrester Wave™: Notebook-Based Predictive Analytics And Machine Learning Solutions, Q3 2018” and see the Forrester report “The Forrester Wave™: Multimodal Predictive Analytics And Machine Learning Solutions, Q3 2018.”

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