For Coders and Non-Coders: Break Into Deep Learning with Python and IBM Watson Studio

Session 2223

Lab Exercise Guide

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1 Getting Started

1.1 About This Lab

A warm welcome to Think 2021—From myself and my colleagues across IBM, we're thrilled to have you here!

Our goal in this 2-hour lab session is to introduce you to wide world of Deep Learning, one of the hottest subfields in Machine Learning and Artificial Intelligence, and a set of technologies that is revolutionizing many avenues of business.

As the title suggests, we've designed this lab for a variety of different attendees—those who have a background in programming, but also those who don't. While we will be dealing with code during this session, it's totally fine if you don't have any experience in programming—We'll be providing instructions in this guide and in the presentation to help you follow along.

Both coders and non-coders will come away from the session with a strong intuition for what Deep Learning is, how it compares to other approaches in Machine Learning and AI, and the knowledge behind building your own deep learning-based program to classify handwritten digits in images. Above all, we're confident this knowledge will help you recognize the role Deep Learning can play (or already is playing) in your organization.

The first hour of the lab consists of setting up Watson Studio—IBM's award-winning platform for Data Science and AI that we'll use to build our first Deep Learning application, followed by a conceptual introduction to the field. The second hour consists mainly of our coding exercise—building a neural network with Watson Studio and the Python library TensorFlow to classify images of handwritten digits.

This guide will serve as a roadmap for the remainder of the session. Beyond the session, we hope you'll also use the contents of this guide as reference material on the topics we'll be discussing.

1.2 How to Ask for Help

There may be points during the session when you feel confused or uncertain about what's being covered—if this is the case, we'll be more than happy to help you!

You can ask for help by raising your hand using the "Raise Hand" function in the call, at which point you'll be able to share your question(s) out loud during the session. You can also post your question as text in the chat, and an IBMer will respond there.

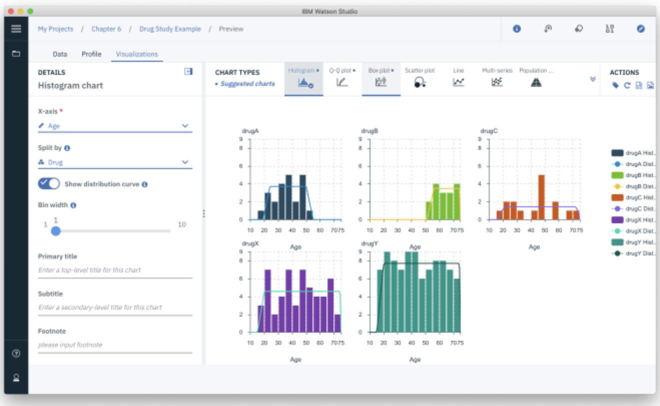
If you have questions or feedback after the session, don't hesitate to reach out to Alex (alexamari@ibm.com) and/or Cedric (cedric.jouan@ibm.com).

1.3 Watson Studio Setup

1.3.1 **What is Watson Studio?**

First things first, the applied part of this lab will require you to download and run code in Python. To view, edit, and run the code we'll be providing, we'll be using a cloud-based Integrated Development Environment (IDE) called Watson Studio.

For non-coders: You can think of an IDE as an interactive editor for code—kind of like a document processor for a writer or photo-editing software for a photographer. The "cloud-based" part of Watson Studio means that the actual computing that's going on behind the scenes (the number crunching involved in actually running our programs) is taking place on a powerful computer at one of IBM's global data centers. This means we can use Watson Studio to run programs far faster than our everyday laptops and desktops (our "local" devices) ever could. This is one of the main reasons why us Data Scientists use tools like Watson Studio to write, edit, visualize, and test our programs.



In this session we'll be running a relatively basic Python notebook in the free, lite version of Watson Studio which you can access on your preferred web browser. Keep in mind that Watson Studio is chock full of features to streamline all aspects of enterprise data science. If you're a Data Scientist, be sure to learn more about Watson Studio at https://www.ibm.com/cloud/watson-studio.[1]

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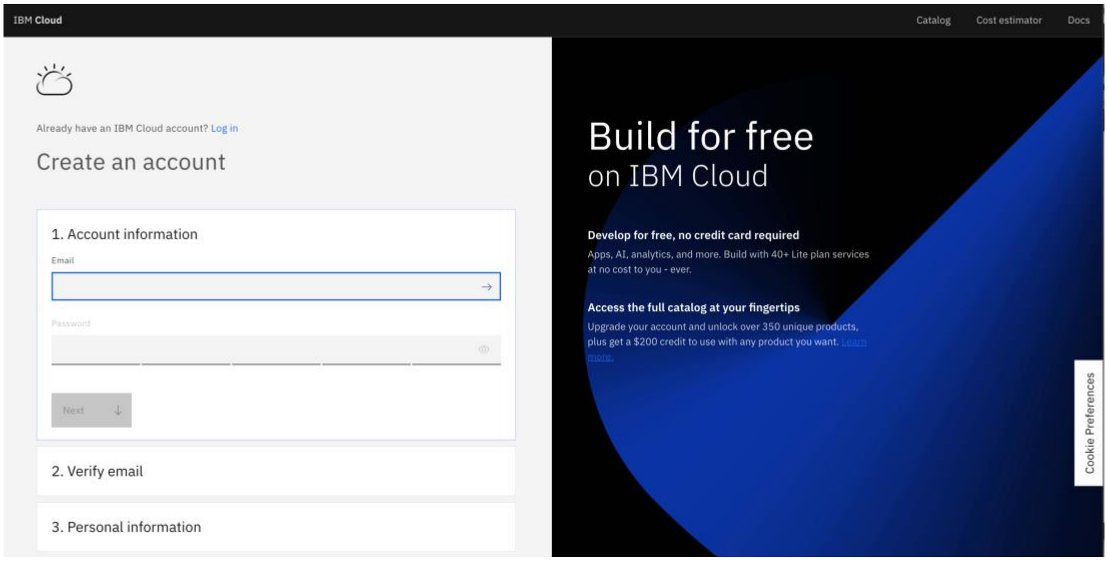
[1] A note for experienced coders: We'll be conducting our exercise with a standard .ipynb notebook file, meaning you may run the notebook in another IDE (such as a local environment). That being said, we'd strongly recommend following along with Watson Studio, as it comes with all of the necessary libraries pre-installed. Using Watson Studio also means we'll be better able to help you with your code if you run into any issues!

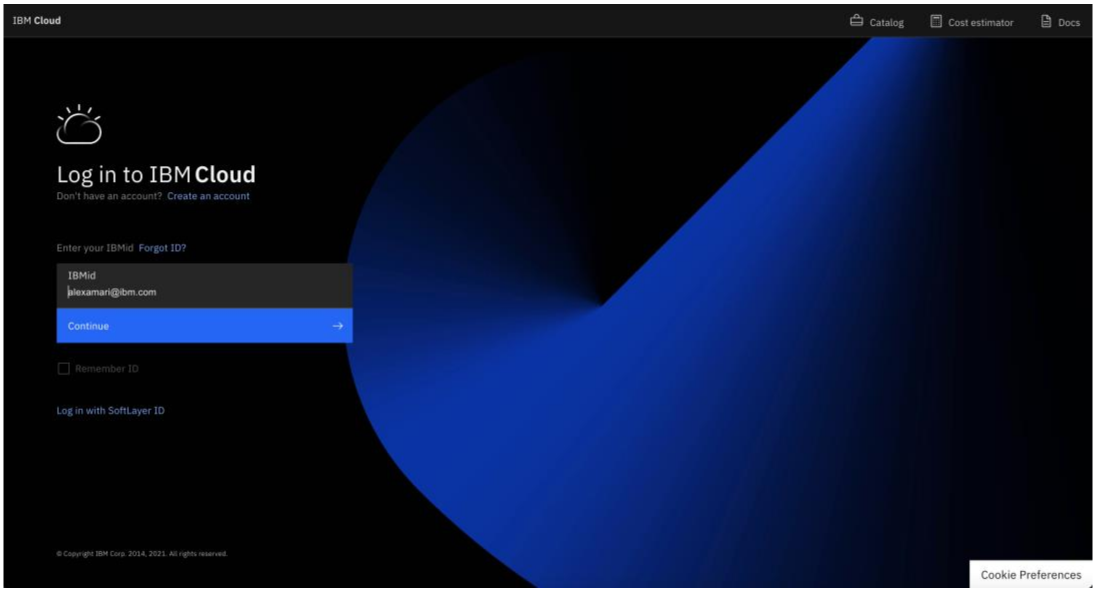
1.3.2 **Installing Watson Studio**

Setting up the lite version of Watson Studio is quick, easy, and of course free! It won't require you to download any new software on your computer. Here are the steps to get set up:

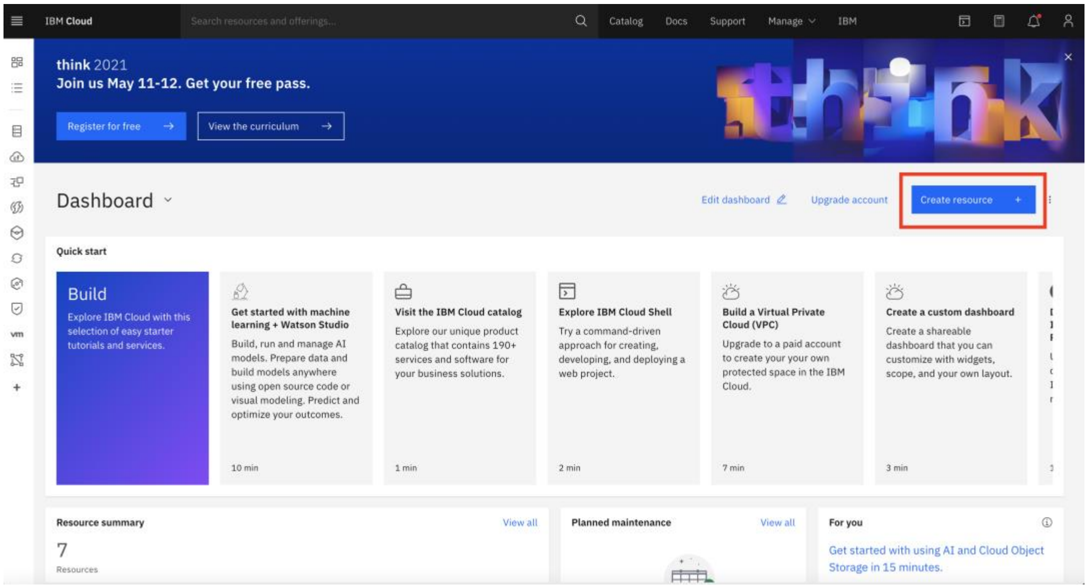
1. Get your IBMid: If you do not have an IBMid, [you may sign up for one here](#).



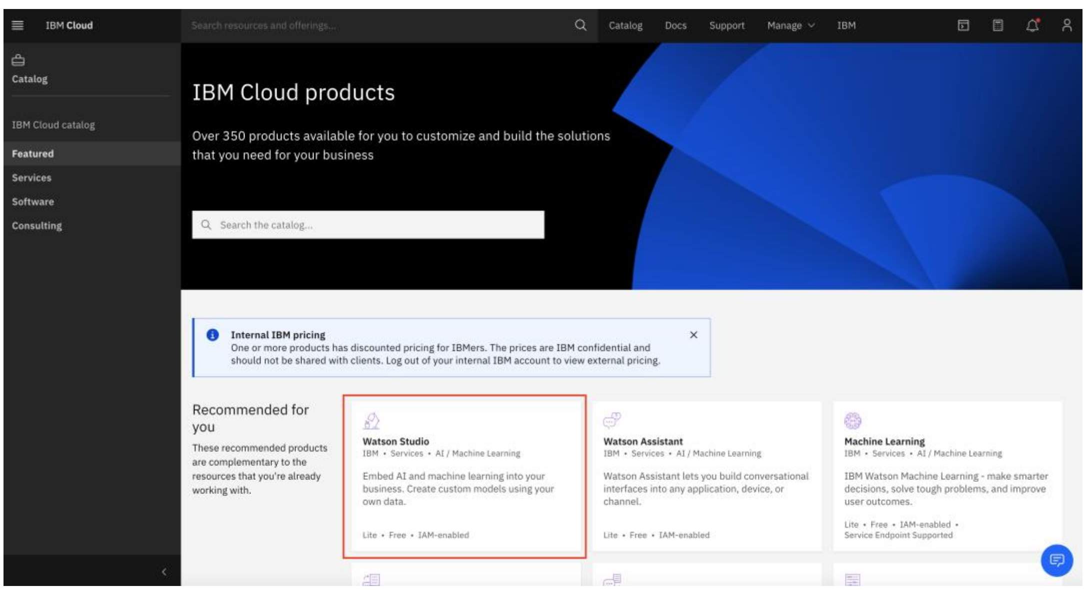
2. Log into IBM Cloud: Once you have your IBMid, [log into the IBM Cloud](#).



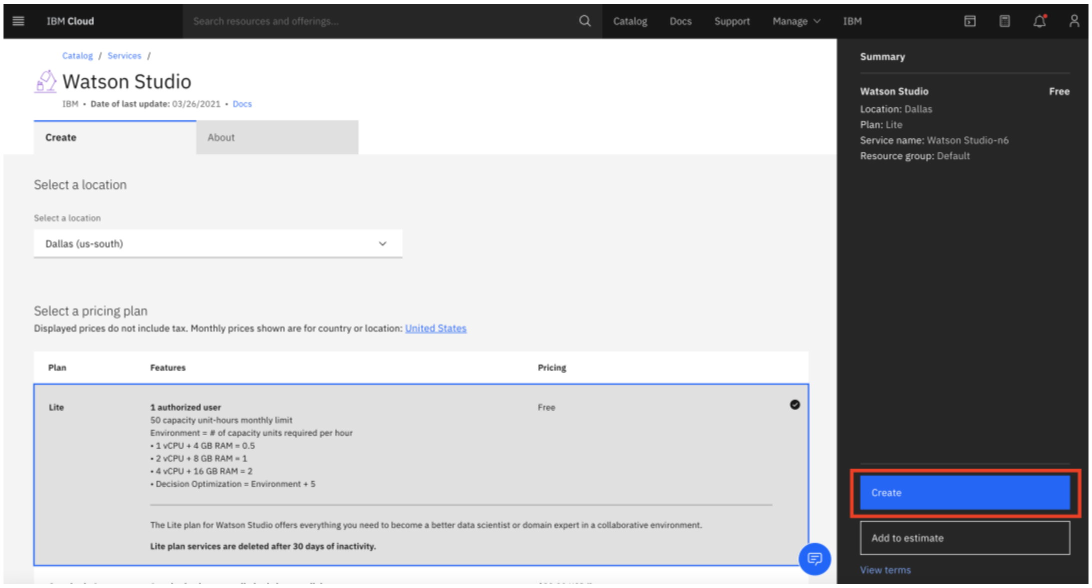
3. From the Dashboard, select “Create a Resource”



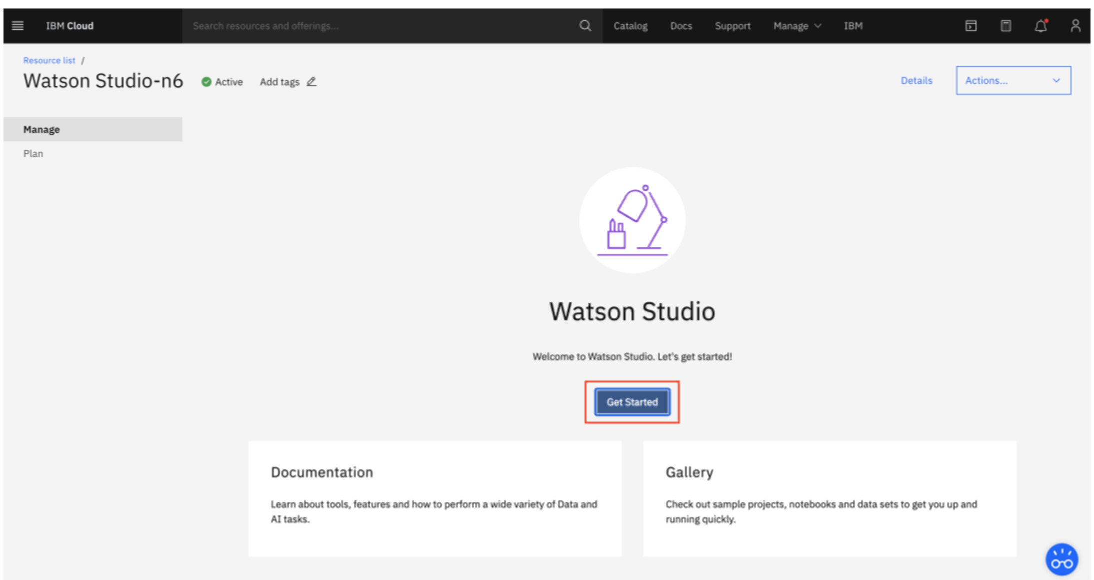
4. Select “Watson Studio” from the products page



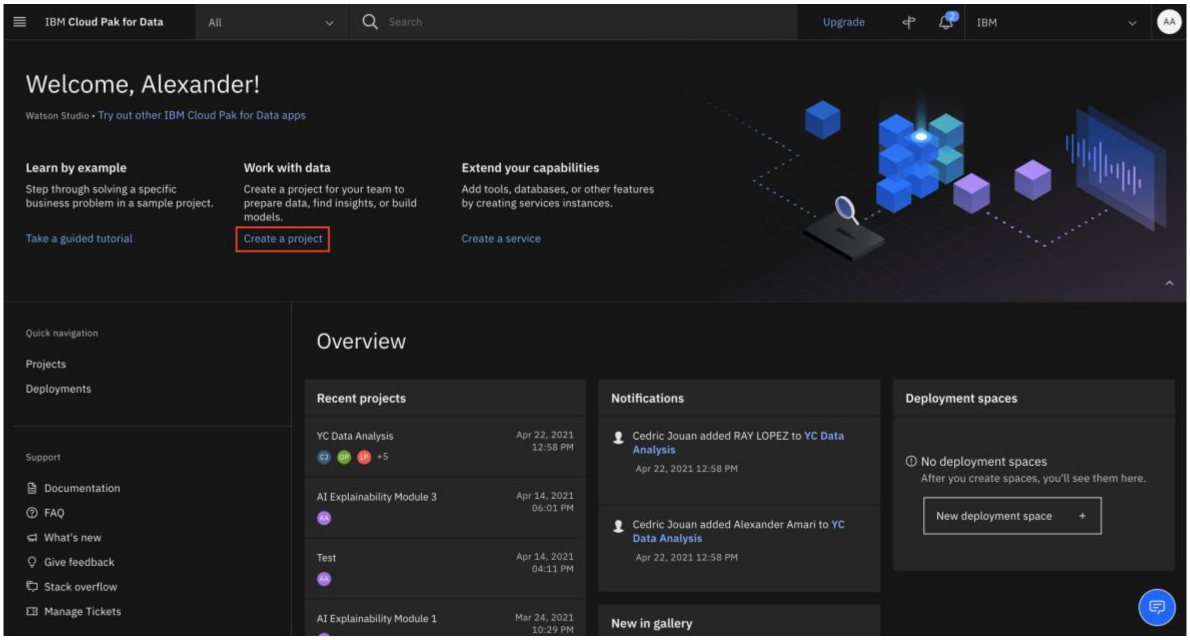
5. Under Select a location, please select the server location that is closest to you (for example, Dallas us-south). Under Select Pricing Plan, select “Lite”, then click “Create”



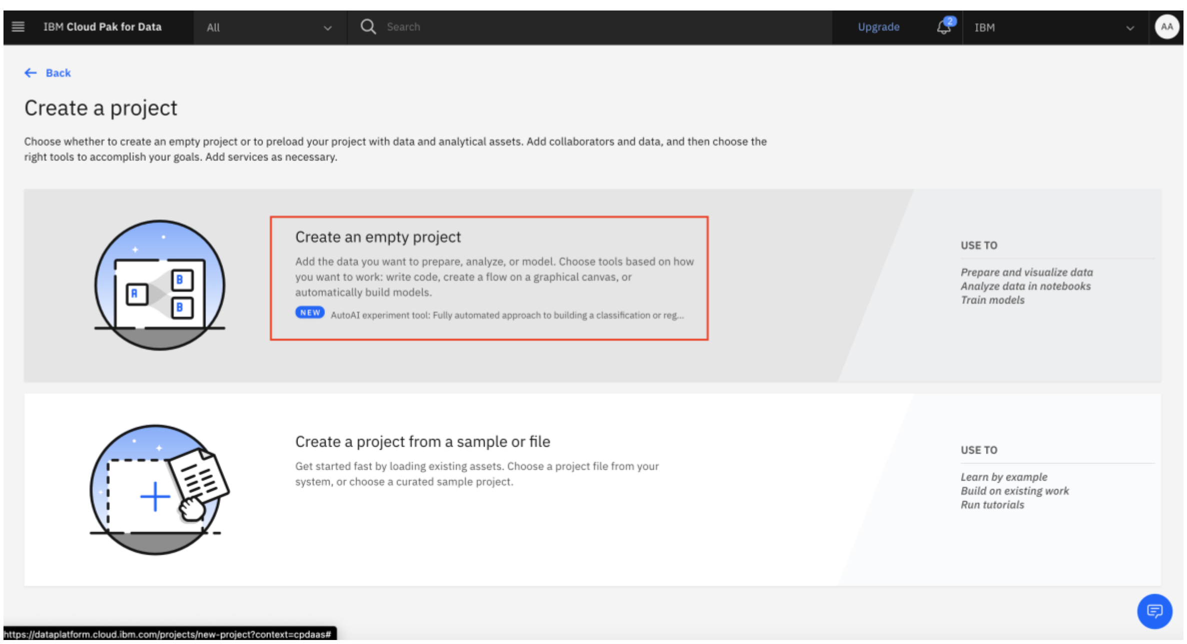
6. Click “Get Started”



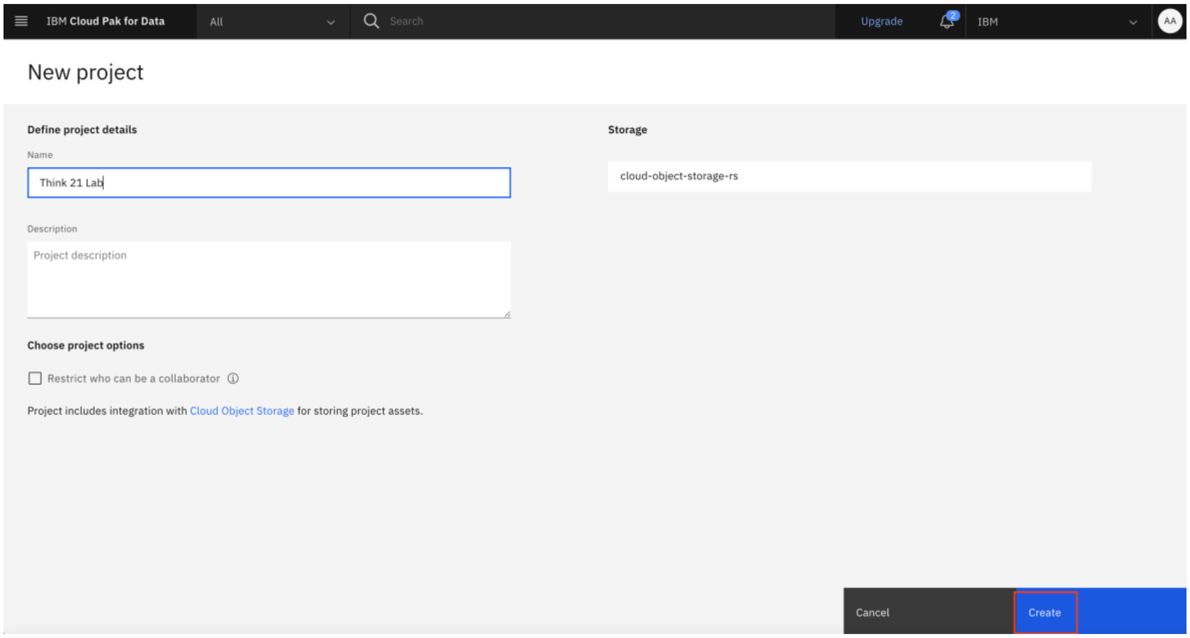
7. Once you reach the Cloud Pak for Data dashboard, select "Create a project"



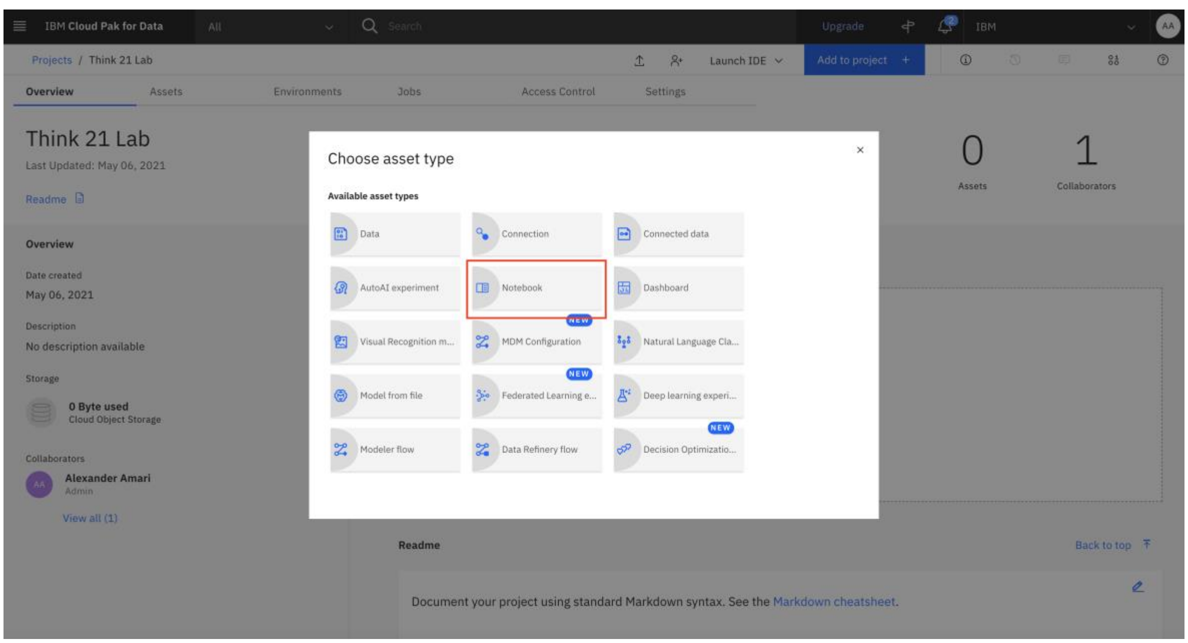
8. Select "Create an empty project."



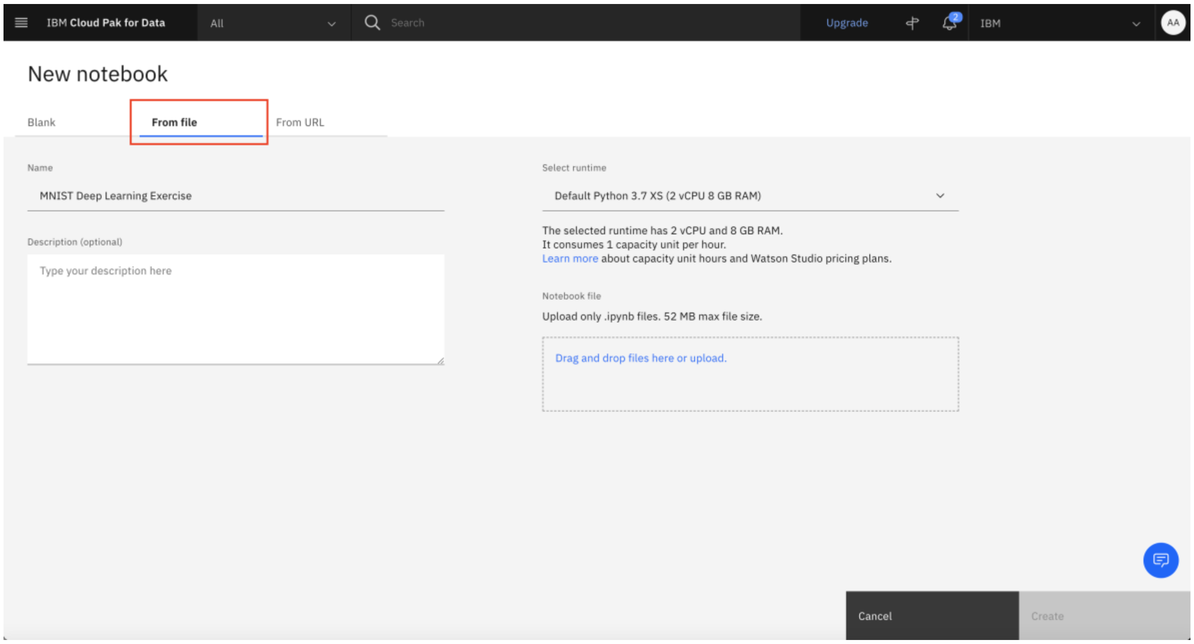
9. You can choose a Name and Description for the project, such as “Think 2021 Lab.” Then select “Create”



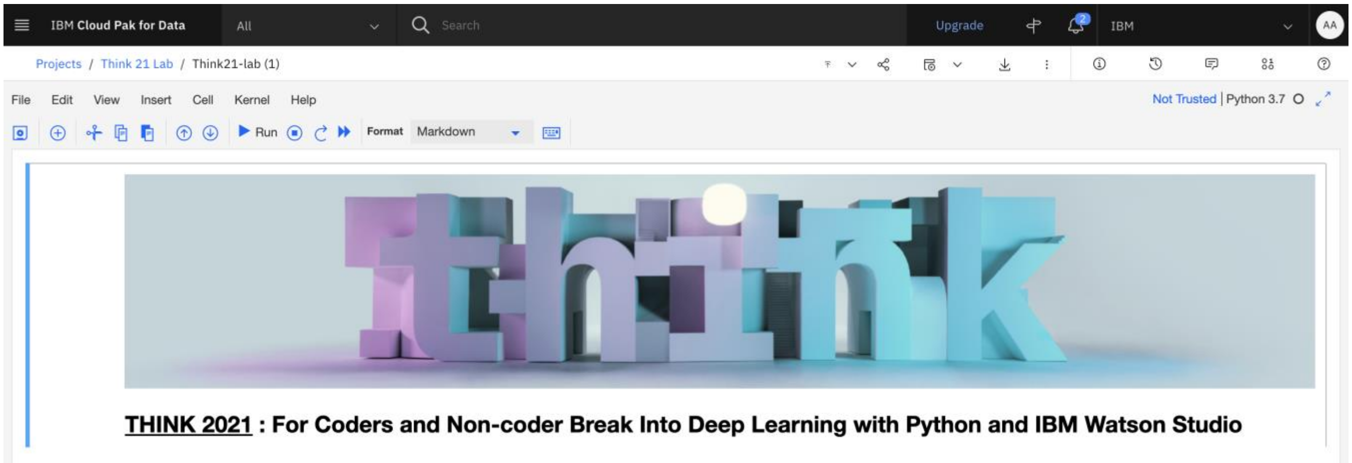
10. Select “Add to project” and in the pop-up menu select “Notebook”



11. On the top-left, select "From file." In the name field, enter a name such as "MNIST Deep Learning Notebook." Then drag the .ipynb lab file to the right pane and select "Create"



12. Upload the .ipynb file Think21-lab2223.ipynb. You should see something like this:



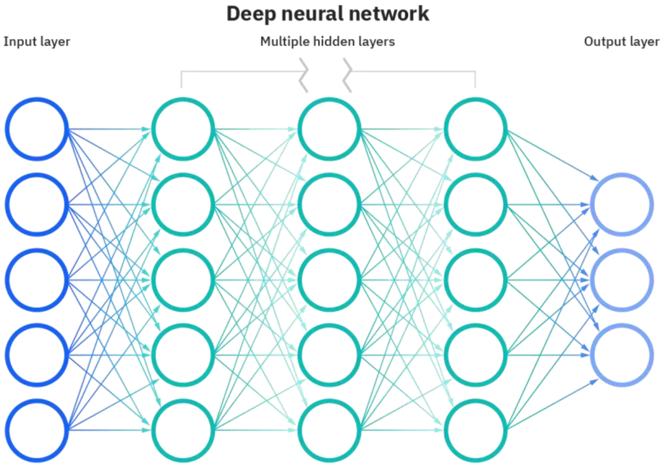
And that's it for our setup! Remember, if you're having trouble, please don't hesitate to ask for help in the Lab Session chat and an IBMer will be right with you.

2 Introducing Deep Learning

2.1 AI vs. Machine Learning vs. Deep Learning

Let's begin with a brief talk on the relationship between Artificial Intelligence (AI), Machine Learning, and Deep Learning. You're probably already somewhat familiar with AI, but to give it a precise definition, we'll paraphrase one developed by two of the leading experts in the field, Peter Norvig and Stuart Russell. They define **AI** as the design and building of intelligent agents (computer systems) that take information from an environment (data) and use it to take actions that affect that environment.

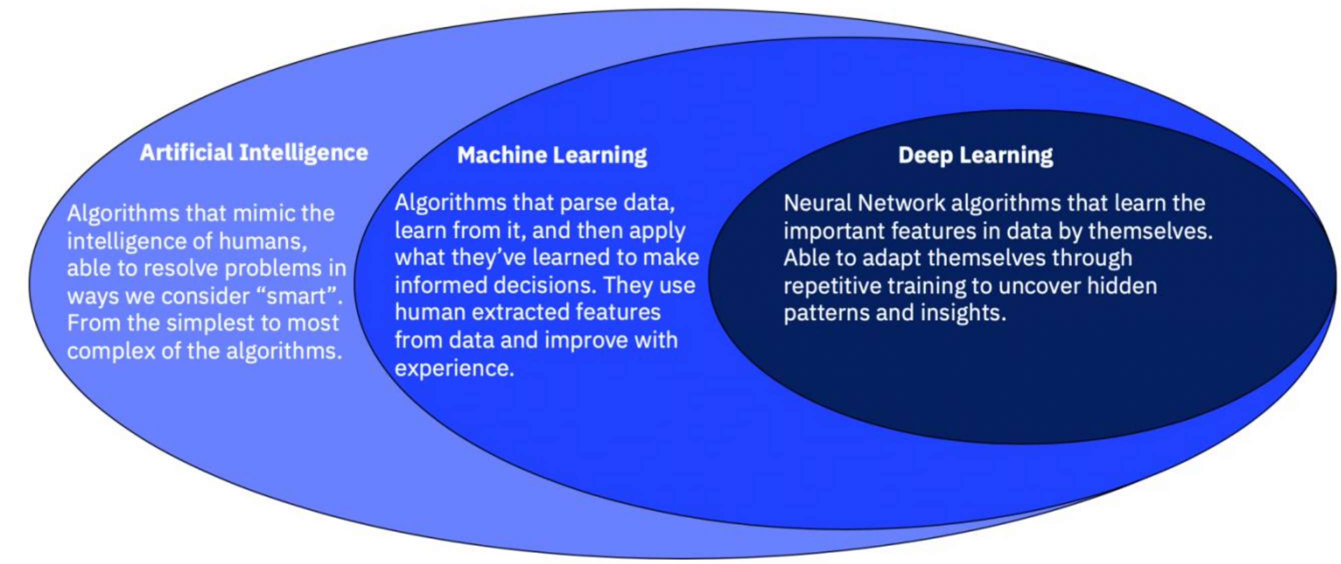
What about Machine Learning? The term refers to a broad set of computer algorithms (processes or sets of rules followed in calculations) that form this bridge between the inputs (data) the outputs (predictions, classifications, etc.) of AI systems. Another more formal definition for **Machine Learning**: "The study of computer algorithms that improve automatically through experience and by the use of data."[2] When people talk about AI, they're almost always talking about systems built using machine learning. Indeed, advances in machine learning are the main reasons why we've seen such a huge rise in interest in AI over the past decade or so.



And finally, Deep Learning. **Deep learning** is a simply a subset of machine learning that focuses on a specific kind of computer algorithm known as the **artificial neural network.** The word neural derives from neuron, the fundamental type of cell in our brains. So as the name suggests, these neural networks attempt to simulate the behavior of the human brain—albeit far from matching its ability—allowing it to "learn" from large amounts of data. Neural networks can consist of one or multiple layers of "neurons," and adding more layers tends to increase the network's ability to successfully perform whatever task we're trying to get it to do (such as classifying images—e.g. is this a picture of a dog or a cat?). When a neural network contains more than one intermediate "hidden" layer, it is said to be a "deep" neural network. Hence, the term "Deep Learning."

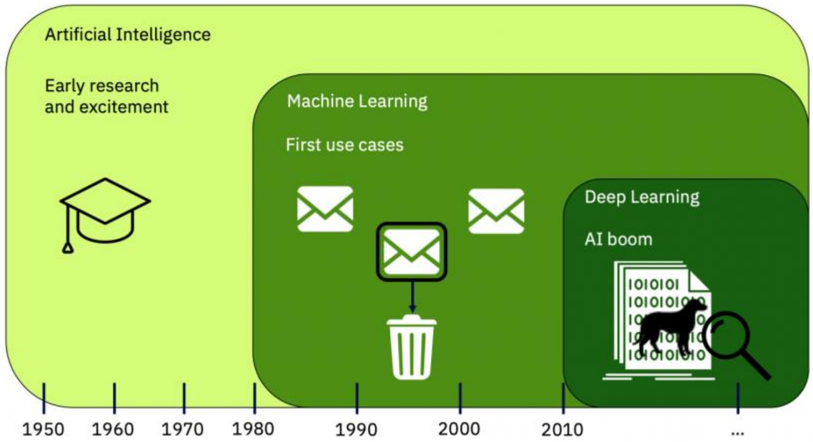
[2] Mitchell, Tom (1997). *Machine Learning*.

We'll be talking much more about neural networks for the remainder of this lab, but for now you can think of the relationship between AI, Machine Learning, and Deep Learning in terms of this (crude) diagram.



2.2 Why Deep Learning? Pros and Cons

The approaches behind Machine Learning and Deep Learning have actually existed for quite some time. Around the 1980's the field of AI began gravitating strongly towards Machine Learning, focusing on what we now call "Classical" ML algorithms and approaches. Similarly, the artificial neural networks that we use today were conceived as early as the 1970's. However, the field of AI did not fully embrace Deep Learning until the early 2010's—after which we've seen an explosion of Deep Learning use cases and applications.



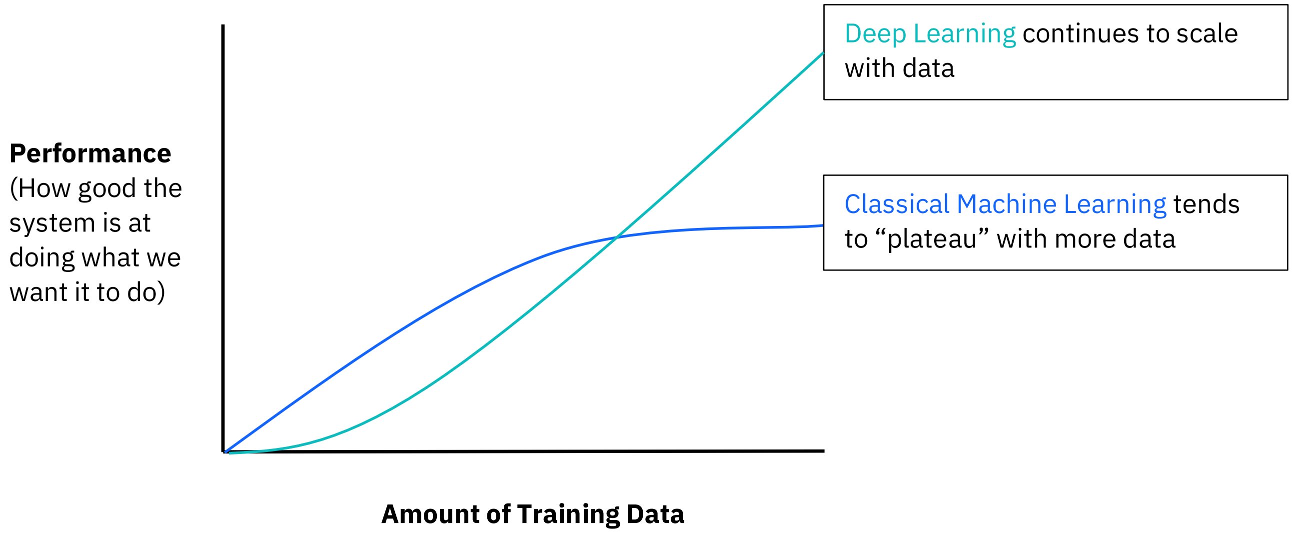
The main reason for this shift is that Deep Learning is computationally expensive—more so than most classical Machine Learning approaches—and it's only been in the past decade or so that computers became powerful enough to make neural networks practical. Similarly, neural networks rely on large amounts of "training data" to work well. More powerful computers mean that more data can be collected—and ultimately used to train neural networks.

Deep Learning Pro #1: Performance

Although it is computationally and data-intensive, Deep Learning often outperforms classical Machine Learning approaches. And there are some tasks that lend themselves particularly well to neural networks. For example, Deep Learning has proven extremely effective at image classification tasks—grouping images based on what they're of e.g., "dog" or "cat."

Deep Learning Pro #2: Scaling

Another major strength of Deep Learning is the fact that many neural networks scale extremely well with data, meaning that they get better and better at doing their job when more data is provided to them for training. This is in contrast to many classical Machine Learning algorithms, which tend to provide "diminishing returns" in terms of performance when provided with more data. In a world where more and more data are being produced and processed every day, this makes Deep Learning the preferred approach to many AI use cases.



Deep Learning Con #1: Computation

The pros of Deep Learning flow naturally into its major cons. As we've already seen, Deep Learning is computationally expensive when compared to many other Machine Learning approaches. Neural Networks also tend to be quite data intensive: In as much as they scale well with large amounts of data, they also require large amounts of initial training data to work at all. In the diagram above, notice how Deep Learning actually underperforms Classical approaches a certain point of training data is available. In many real-world use cases, we lack the data and/or computational resources to make a Deep Learning approach practical.

Deep Learning Con #2: Explainability

Another common issue facing those seeking to leverage Deep Learning approaches deals with explainability—or the lack thereof—in Neural Networks. The gist here is that even if we can build a neural network to perform a task very well, it is often very difficult to understand *how* the system is actually producing its results. This problem is compounded when we make neural networks more complex (for example, by adding more hidden layers, which we'll see later). This is why neural networks are sometimes referred to as "black box" models—we see what goes in, and what comes out, but it's hard for us to understand what's going on inside. In use cases where transparency is essential—such as in cases where an organization needs to be able to explain *why* their algorithm approved a loan, rejected an application, chose an image, and so forth—Deep Learning can become problematic. The good news is that progress is being made in making Deep Learning models more transparent: Explainability in Deep Learning is an area of active research at IBM Research and in AI labs around the world. If you're interested in this topic, be sure to read more on IBM's initiatives in Explainable AI.

2.3 (A Few) Deep Learning Applications for Business

Now that we've defined Deep Learning, compared it to other kinds of Machine Learning, and discussed some of the pros and cons of neural networks, we can now look at some of the ways Deep Learning is being used to add value to businesses. In truth, real-world Deep Learning applications are a part of our daily lives, but in most cases, they are so well-integrated into products and services that we're unaware of the complex data processing that is taking place in the background. Here are just a few examples of Deep Learning in action:

Law enforcement

Deep learning algorithms can analyze and learn from transactional data to identify dangerous patterns that indicate possible fraudulent or criminal activity. Speech recognition, computer vision, and other deep learning applications can improve the efficiency and effectiveness of investigative analysis by extracting patterns and evidence from sound and video recordings, images, and documents, which helps law enforcement analyze large amounts of data more quickly and accurately.

Financial services

Financial institutions regularly use predictive analytics to drive algorithmic trading of stocks, assess business risks for loan approvals, detect fraud, and help manage credit and investment portfolios for clients.

Customer service

Many organizations incorporate deep learning technology into their customer service processes. Chatbots—used in a variety of applications, services, and customer service portals—are a straightforward form of AI. Traditional chatbots use natural language and even visual recognition, commonly found in call center-like menus. However, more sophisticated chatbot solutions attempt to determine, through learning, if there are multiple responses to ambiguous questions. Based on the responses it receives, the chatbot then tries to answer these questions directly or route the conversation to a human user. Virtual assistants like Apple's Siri and IBM Watson Assistant extend the idea of a chatbot by enabling speech recognition functionality. This creates a new method to engage users in a personalized way.

Healthcare

The healthcare industry has benefited greatly from deep learning capabilities ever since the digitization of hospital records and images. Image recognition applications can support medical imaging specialists and radiologists, helping them analyze and assess more images in less time.

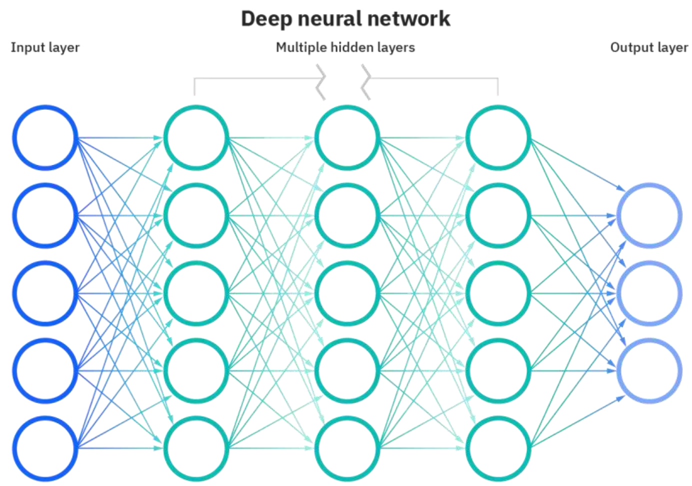
3 Building Blocks of Deep Learning

3.1 Neural Networks

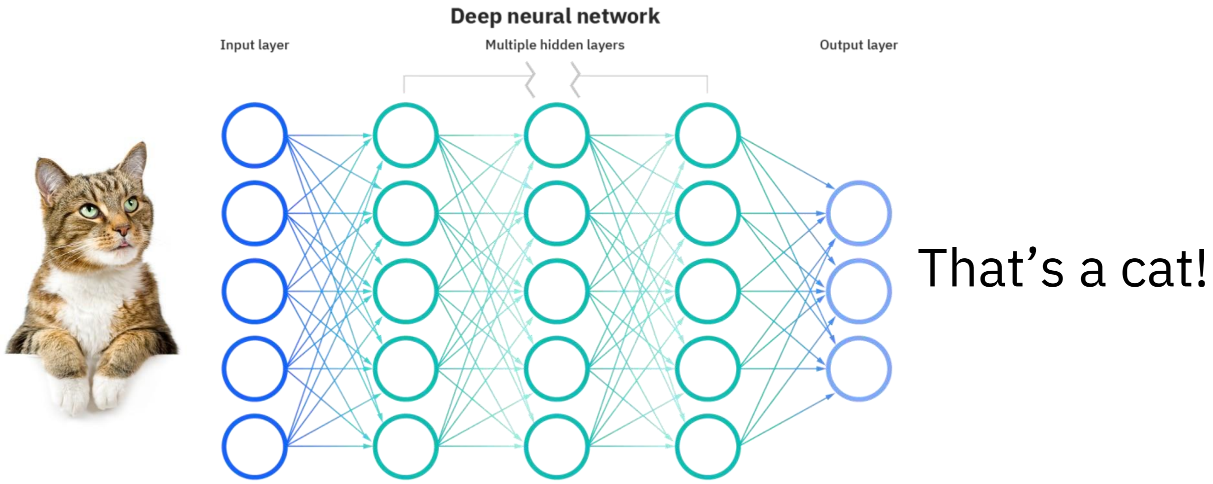
Before we talk about the insides of artificial neural networks, let's take a moment to think about how our own biological neural networks function. If I show you an image of a cat, how is it that you know it's a cat? Of course, most of us would say, "we just know." In fact, if you were to see the electrical and chemical activity going on in your brain, you'd see some pattern in the firing of neurons when your eyes caught glimpse of the cat. Our brains have an amazing ability to take in the visual information from our eyes (which we can think of as data) and send a complex signal across the neurons in various parts of our brain to allow us to recognize what we're looking at. This same type of process is happening as you read these words, and your brain is relating the visual information of the text on this page to a meaning that you can understand.

Now, consider that at some point in your life, your brain could not immediately recognize a cat in an image, or the letters typed out on a document. As a child, your brain had to learn to relate these types of inputs to the understanding that you now have naturally. In fact, the process of learning to recognize a dog or a cat or reading paragraphs in English required the building of complex connections among the neurons in your developing brain—connections that now give you the sense of "I just know," when you see an image, hear a sound, or read a word. This process of learning from inputs to outputs informs how we build artificial neural networks.

Let's return to the Neural Network diagram that we saw earlier.



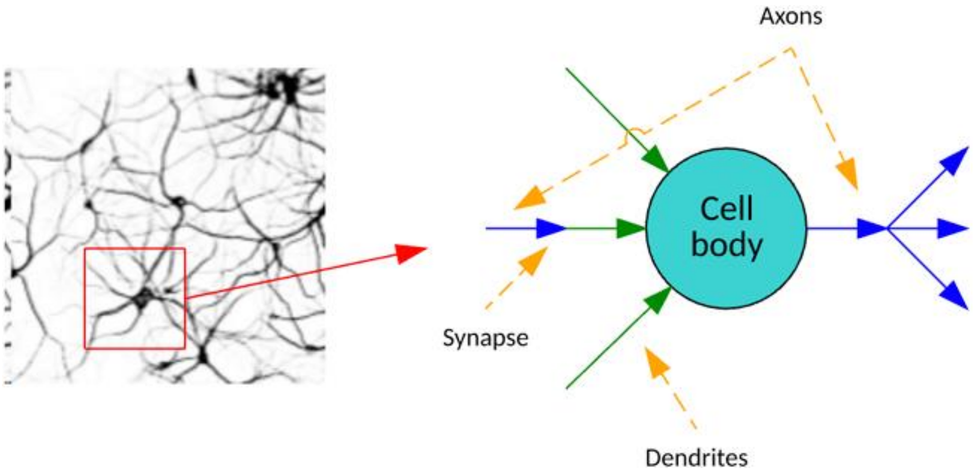
Roughly speaking, we can think of Artificial Neural Networks as analogous to the connections between neurons in our brains. The goal of the entire system is to build a mapping from an "Input Layer" to an "Output Layer." The input layer consists of a single instance or entry of our training data—such as a single image of a dog or a cat, where each neuron is a number representing the color of each pixel in the image—while the output layer can be thought of as the desired output of our network—such as the classification “dog” or “cat.” Again, the idea is we’re making a mapping from our data to a result, and the network is using many examples of training data to make the best possible mapping.



3.2 Neurons

How does the network actually go about making this mapping from data to a desired output? It’s time we take a closer look at the fundamental units of artificial neural networks: Neurons.

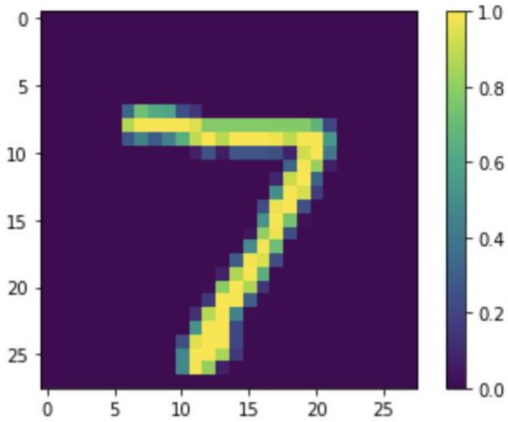
In the brain, biological neurons are highly connected and communicate chemical signals through synapses between axons and dendrites. The human brain is estimated to have 100 billion neurons, with each neuron connected to up to 10,000 other neurons.



So how do artificial neurons compare? For the moment, you can think of **artificial neurons** simply as stores of values between 0 and 1—analogous to those chemical signals in biological neurons. A neuron with a corresponding value of 1 is said to be "activated," like a firing neuron in the brain passing its signal on to another neuron, while a neuron with a corresponding value of 0 is said to inactive.

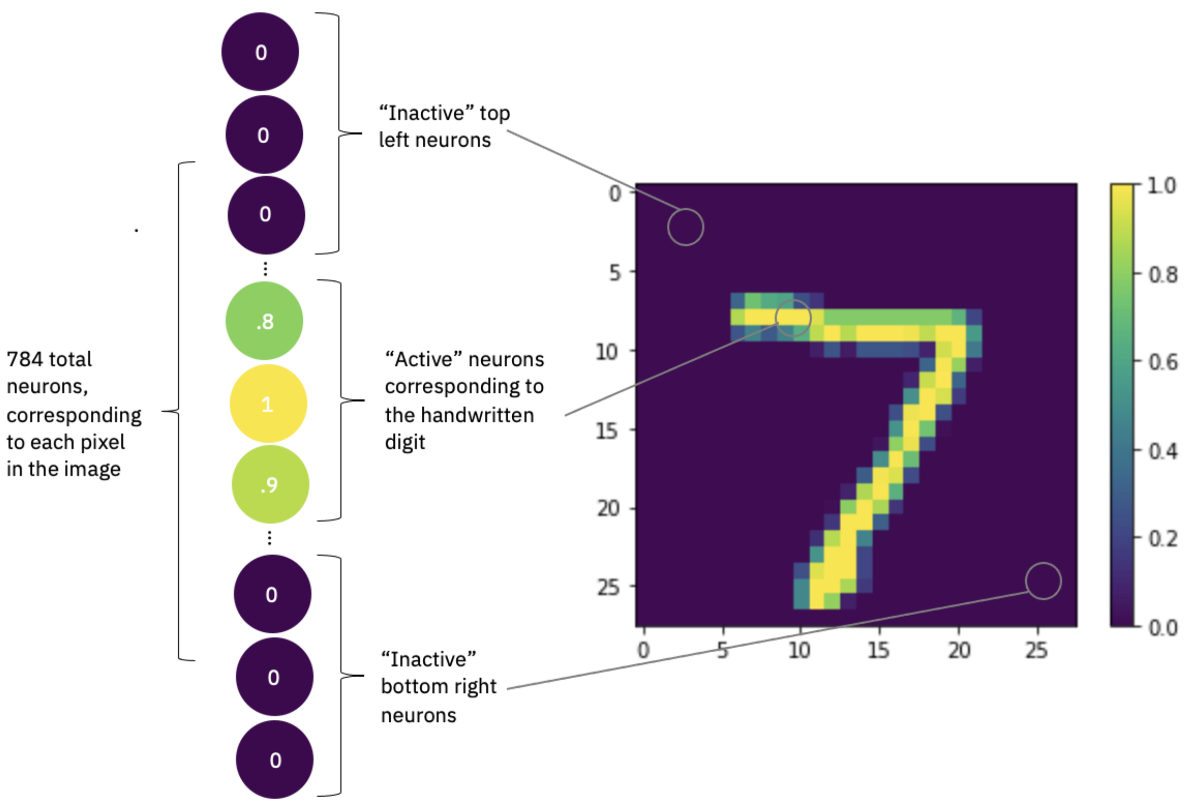
Consider how an input image (like the one of the cat up there) can then be represented as a collection of neurons. We assign each pixel in the image a number between 0 and 1 depending on its coloration, or **activation**.

To see this more clearly, let's look at one of the handwritten digit images we'll be looking at in our coding exercise for this lab.



The image consists of 28x28 pixels, meaning there are 784 pixels in total. Notice how the pixels on the actual "7" are lit up yellow, corresponding with number close to or equal to 1, while pixels that don't have any "7" on them are equal to 0, meaning they're not activated at all.

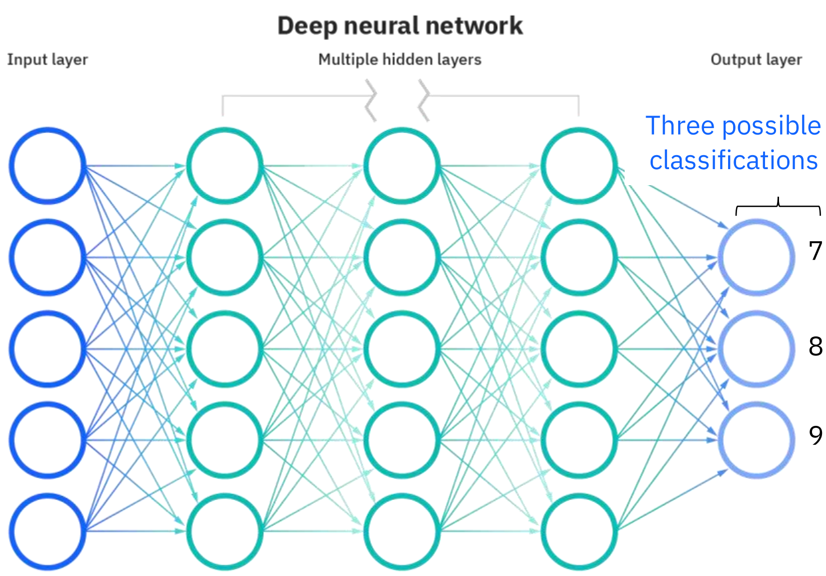
Now, imagine a column of 784-pixel neurons—again, for now just values between 0 and 1—starting from the top left pixel in the image to bottom right. This is how we'd represent this data entry, the digit "7," in the input layer of a neural network.



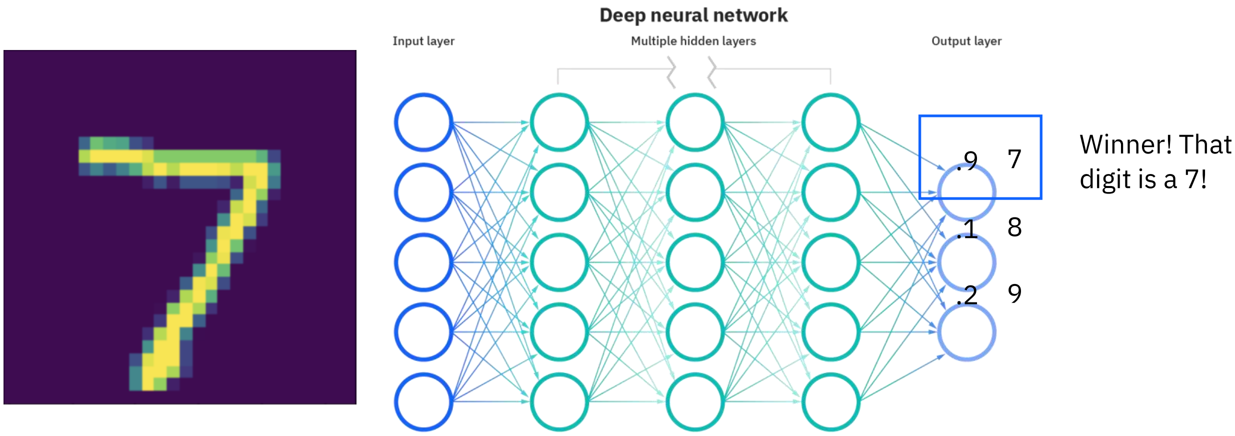
3.3 Layers

Now that we've seen how we represent the information in our data in terms of active and inactive neurons. The stacking of these neurons—which we visually depict as a column—represents a "**layer**." These layers create an ordered sequence for our network, where information "feeds forward" from the **input laye**r to the **output layer**. In truth, there are a wide variety of different neural network architectures which vary the number, size, and order of layers, but for our purposes we'll be focusing on the basic **feed forward** architecture.

When looking at our neural network diagram, you may be wondering why the output layer is smaller (i.e. it consists of fewer neurons) than our input layer (our original pixel neurons). Recall that ultimately, our network is trying to build a mapping from the input (data) to the output, which is whatever we're interested in making the neural network do. So, in a task like classifying handwritten digits, that means that the output layer neurons actually correspond to the neural network's prediction for what a particular digit is.

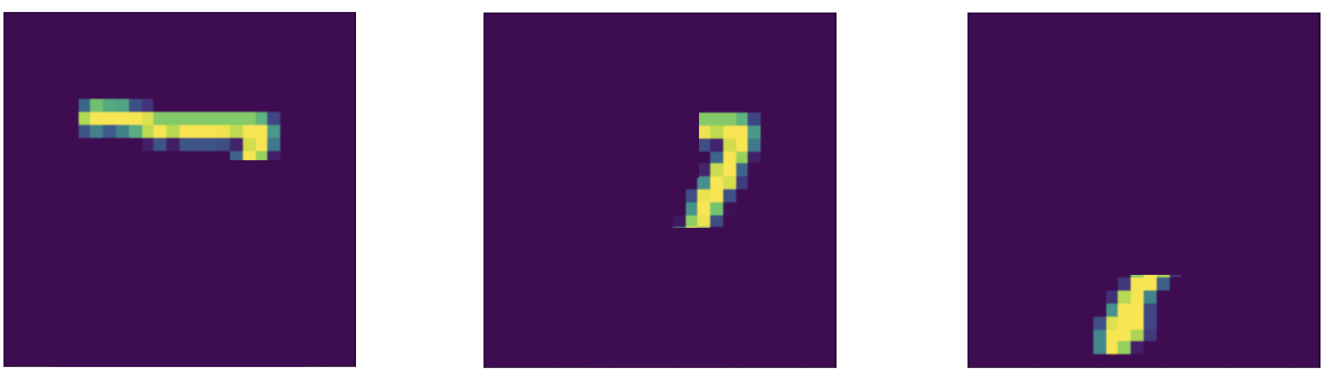


Let's imagine we're trying to get our network to map our digits to one of three numbers: 7, 8, or 9. In other words, we want the network to tell us whether the handwriting we're showing it is a 7, 8, or a 9. Those 3 neurons in the output layer each correspond to one of those numbers. And after the network has received signals (numbers) from the preceding hidden layers—all the way back to our original input digit layer, it too will assign a value between 0 and 1 to each of those final 3 neurons. Whichever neuron has the highest value (activation), will correspond with the networks decision on what the digit is!



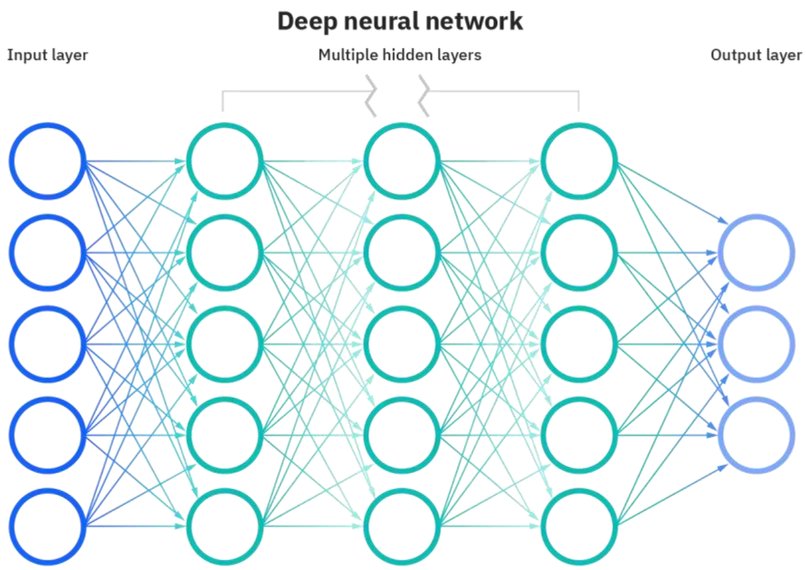
What of the intermediate, “hidden” layers? Again, the network is feeding forward signals from the original input layer to the output classification. Therefore, those signals are actually being passed and transformed through the intermediate “hidden” layers composed also of neurons taking on values between 0 and 1. We can think of these **hidden layers** as possible “pathways” for our network to use as it tries to make the best possible mapping from input to output. The number of hidden layers as well as the numbers of neurons they contain is actually something that we the data scientist can control and change. In practice, finding the best **architecture** for the network to perform its task can be a process of experimentation, trial, and error.

Recall that our input layer corresponds with the pixels in our starting image. What do the hidden layers correspond with? It turns it out it’s not always easy to intuit what the hidden layers actually represent in the “mind” of our artificial neural network. If we were to visualize them—again drawing an image based on the activations of the individual pixels—the hidden layers may look something like these:



We call these “latent” representations of our data. They’re the way that our network “learns” the **latent features** associated with the digits. The network sees an input, maps it through the hidden layer latent spaces, and ultimately produces values for our output layer corresponding with what it believes the digit to be. When you think about it, this is much like how our own brains would process these same data. Even if we don’t realize it, our brains tell digits apart by sending signals corresponding with the features they contain. A circular shape in the digit (potentially captured by one hidden layer) might point your brain to a “0” or an “8.” Two circular shapes in the image (potentially captured by two hidden layers) would be a strong indicator of an “8.” Of course, this all happens subconsciously for us—in a sense the process is “hidden” to us. Hence, the intermediate “hidden” layers of the artificial neural network. The particular combinations of activations in the latent hidden layers are ultimately what allows the network to make its mapping from input to output.

3.4 Connecting Neurons



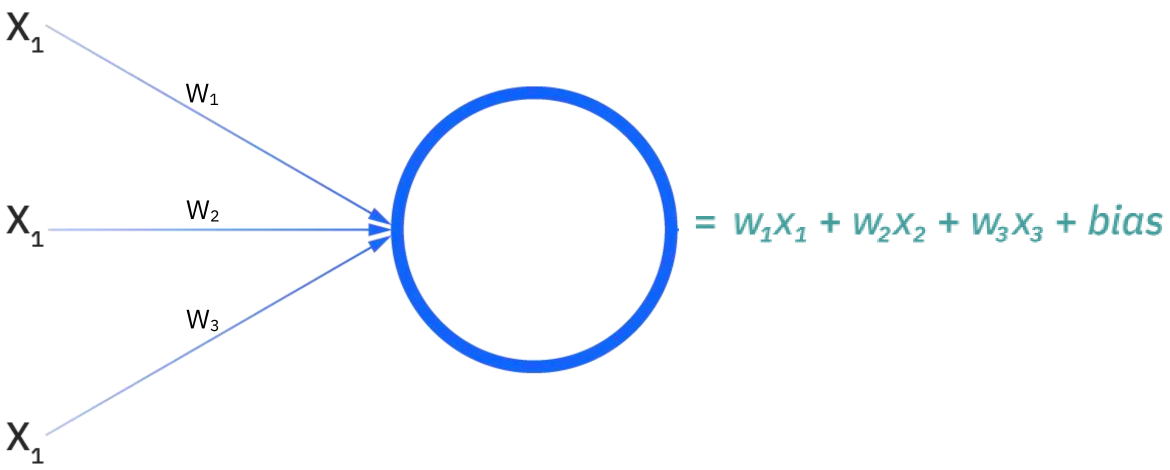
The final component of our neural network that we haven't yet discussed are the connections between the layers of neurons. Notice how each neuron has lines connected to all of the neurons in the previous layer, as well connections to all of the neurons in the following layer. Intuitively, this is how activating signals feed forward through the network. In a fully connected or "**dense**" neural network, such as the ones we'll be dealing with in this lab, each neuron receives information from every neuron in the preceding layer. Likewise, it passes on information to every neuron in the succeeding layer. Remember that every neuron throughout the network takes on a value between 0 and 1. Apart from the input layer (which takes its values from the original input image), each other neuron will be assigned a value according to the information it's receiving from the previous layer's neurons.

The mechanism by which a neuron's activation is determined—based on the sum of all the information from the previous layer—is a mathematical function of what are known as "**weights**" and "**biases**" which compose the connections between neurons. This is the only formula we'll be dealing with in this lab, and it's okay if you don't recognize some of the symbols that it contains.

$$\sum_{i=1}^{m} w_i x_i + bias = w_1 x_1 + w_2 x_2 + w_3 x_3 + bias$$

For now, just know that the left side of the equation represents the actual activation of each neuron—the value we assign to it—so, as we've seen, a number between 0 and 1. That value is equal to the right side of the equation, which we can think of as existing in each and every one of the connections between neurons in our network. On this right-hand side, the X terms, i.e. X_1, X_2, and X_3 represent the values of the neurons feeding into our new neuron. Meanwhile the W terms, i.e. W_1, W_2, and W_3, correspond with the "weights" or "importances" the network assigns each of those preceding activation values. For the moment, you can ignore the "bias" term on both sides of the equation—this term just seeks to constrain the ultimate output of the equation to ensure it leads to a value between 0 and 1.

In this case, we're calculating a neuron based on information from 3 neurons in the previous layer, hence 3 X terms and 3 W terms. If we were to zoom in on such a neuron it might look something like this:



Therefore, a neuron's activation is calculated as the sum of all of the previous neuron activations, multiplied by the weights that the network has assigned to them, plus some bias term.[3] And this value in turn becomes a new X_1 (or X_2 or X_3) that gets input into the following layer, all the way until the output layer when a final result is produced.

So, what really are these weights assigned to the values of neurons as they send their signal to the next layer? You can think of them again as "importances"—or how important our network believes each signal should be in determining the value of a receiving neuron. If a weight has a low value, that means the network believes it is relatively unimportant in determining the next neuron (thus, a smaller W term means that the whole product will be smaller as well). And vice versa, a higher weight indicates that the network assigns a lot of importance to this particular signal.

3.5 Learning the Right Weights

Recall that we have been thinking about neurons and layers as the potential pathways a neural network can use to make a mapping from a particular input to a (hopefully) correct output. Ultimately, then, we can think of the weights of the neural network as the actual pathway that the network ends up choosing. In other words, weights are the way the network actual builds a route to send information through the layers and neurons to an output.

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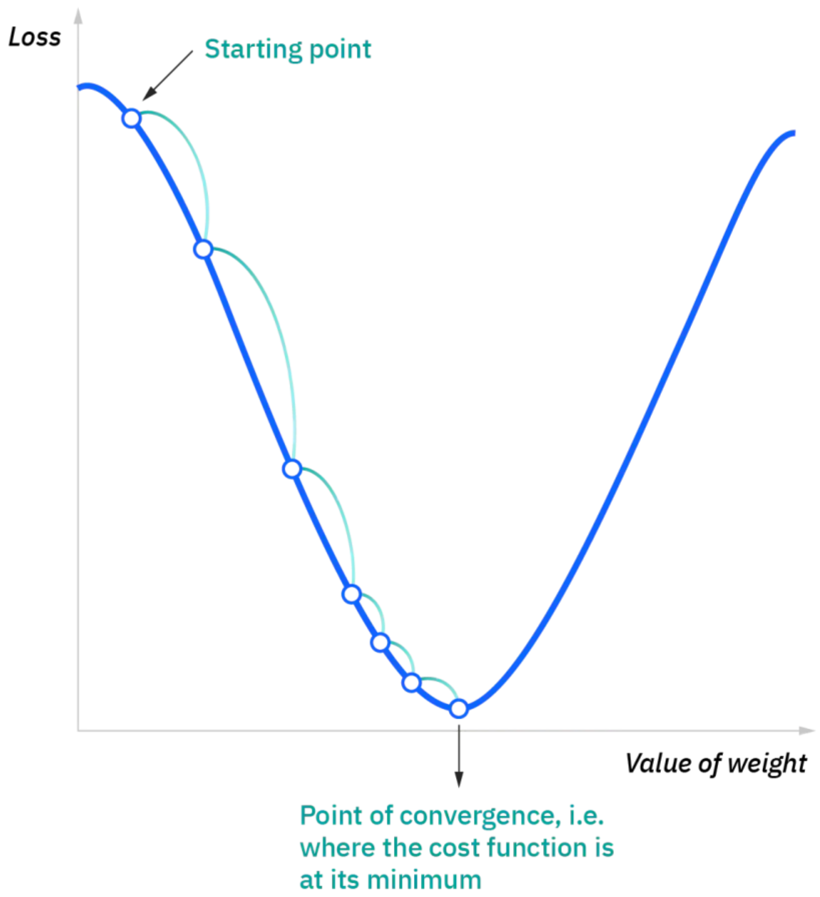
[3] In practice, there is an additional step whereby the output is "squished" through a given "activation function" to ensure the value ends up between 0 and 1, but we don't need to worry about that for now.

But how does the network know which weights to use? Remember that each connection from one neuron to another carries with it an assigned weight. That means that for just two layers each consisting of 784 neurons, the network will have to assign 784 * 784 = 614,656 weights! The process of finding the optimal values for these weights, such that the network is as effective as possible in making correct predictions, is where the “learning” part of Deep Learning comes in. The precise mathematical process whereby this happens is beyond the scope of this lab. However, the intuition behind what’s going on is surprisingly simple.

Essentially, the “training” of a neural network with “training data”—the data the network uses to learn—is the process of allowing the network to try many different combinations of weights between its neurons and layers and adjusting them in a way that makes its ultimate predictions as accurate as possible on the “test data”—the data we use to test how good the network is at the task. More specifically, the network is trying to tweak the weights in such a way that it minimizes its “loss”–a numerical representation of how wrong it is in making its predictions. For example, if the network predicts 60% of the images in the test data correctly, then it’s loss might be something like 0.4.[4] If it predicts 65% correctly, the loss might then be 0.35. The network’s goal is to choose weights such that the loss is as low as possible, i.e. it is as accurate as possible in making its predictions.



We can visualize this process with a diagram like this one. The Y-axis is the overall loss, which is again the measure of “how wrong” the neural network was in its predictions. The X-axis is the value of a particular weight for the connection between two neurons somewhere in the network.

Notice how at the “Starting point”—the network’s first try at predicting the test images—the loss is quite high. This means the network didn’t do a very good job of predicting the digits.[5] Each subsequent point on the line represents the networks next attempt at predicting the test data, after it has gone about incrementally changing the value of the weight. Each of these iterations, whereby the network updates its mapping with new weights,

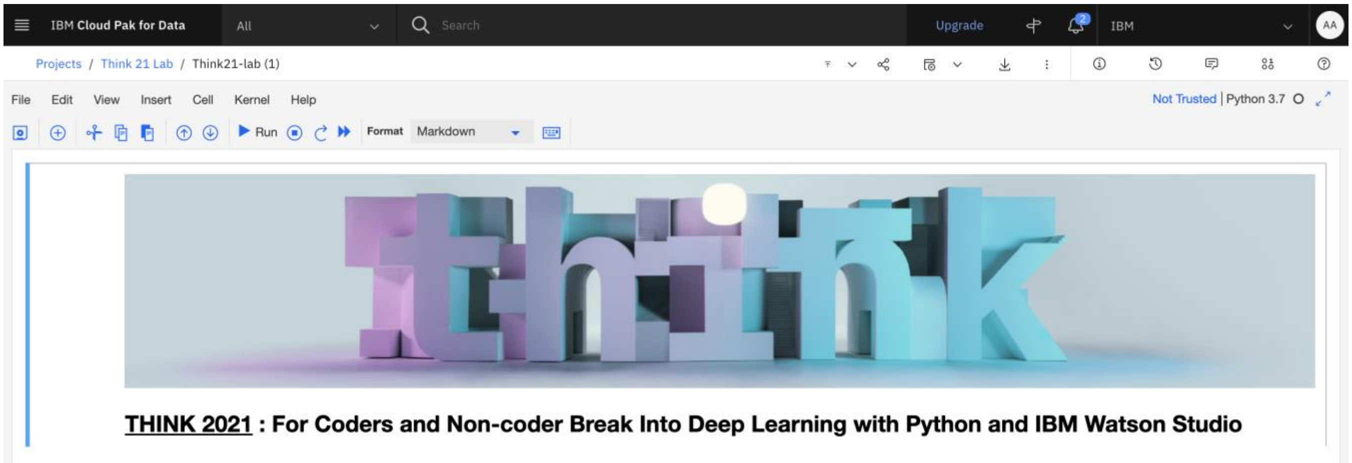
[4] We say “something like” here because there are a number of different approaches to calculating the loss in a neural network, which we call “loss functions,” and these will affect what the precise loss value.
[5] In most cases, the initial weights used across the neural network, i.e. before any training has begun, are assigned randomly, which is why the loss is quite high. In practice, other strategies are sometimes used to set the starting weights in a process known as “**weight initialization**.”

is known as a “training epoch”—which is simply a pass through the training data. In this simple example, the network is only running through seven training epochs (corresponding with the seven points on the blue curve). In practice, neural networks may go through hundreds, thousands, or even millions of training epochs depending on their complexity. Regardless of how many epochs are used, the network’s goal is to “descend” down the “gradient” of this loss function until it finally converges to a point where the loss or “cost function” is minimized (as small as possible). This is the process of “gradient descent”—the main mechanism by which neural networks learn using data!

Neural networks learn by conducting immense gradient descent optimizations across thousands, millions, and sometimes even billions of weights. Furthermore, although we’re using a simple two-dimensional diagram to depict this process, in reality neural networks conduct this optimization process *with respect to* more than one weight in each training epoch. In other words, the network is trying to find the minimum possible loss for some function involving N number of weights. That N controls the dimensionality of the loss function—which we can’t really visualize once it goes beyond three! Recall our earlier discussion about the fact that neural networks are computationally expensive—hopefully this section has put that truth into greater perspective.

4 Coding Neural Networks

The next phase of the lab will be conducted using the lab Python Notebook in Watson Studio. Please ensure you've followed the setup instructions in section one and are looking at this page in your browser:



5 Glossary and Conclusion

Artificial Intelligence: The design and building of intelligent agents (computer systems) that take information from an environment (data) and use it to take actions that affect that environment

Machine Learning: The study of computer algorithms that improve automatically through experience and by the use of data

Deep Learning: The subfield of Machine Learning focusing on building artificial neural networks to train systems to accomplish complex tasks; The technology underlying many of the most successful AI applications, such as self-driving cars

Artificial Neural Networks (Neural Networks): The fundamental approach in Deep Learning; Computer algorithms aimed at mimicking the ways that biological brains send information across brain cells (neurons) as part of information processing. They consist of primarily of layers of artificial "neurons" and the connections between them

Feed-Forward Neural Networks: Neural networks which pass information forward from a starting "input layer" to an ultimate "output layer" (without cycling backwards at any point in the process); The oldest and most fundamental neural network "architecture"

Artificial Neurons (Neurons): A store or "node" of information in a neural network, generally calculated according to signals received from connected neurons in a previous layer

Layers: A series of neurons representing one step during the sequential processing of a neural network; an architectural parameter of neural networks

Input Layer: The left-most "starting layer" in a neural network, corresponding with instances of training data

Output Layer: The right-most "final layer" in a neural network, corresponding with the network's final prediction or classification, e.g. which digit is contained in an image provided in the input layer

Classification: In Machine and Deep Learning, the algorithmic task of predicting class labels for given examples of input data, where classes may be categories such as "dog or cat" or "digits between 0 and 9."

Hidden Layer(s): Intermediate layers in a neural network between the input and output layers, representing latent features used by the network to perform its given task

Training Data: Data used to train neural networks and other machine learning algorithms; Used by neural networks to conduct gradient descent when attempting to minimize overall loss for a particular task

Testing Data: Data used to test the performance of a trained neural network

Loss: Quantitative measure of overall "wrongness" in the outputs of a neural network; Calculated using a variety of "loss functions" chosen by the data scientist depending on the task

Training Epoch: A neural network's single pass through of a training dataset, after which weights are adjusted to minimize overall loss; A parameter that we as the developer choose—most neural networks train over the course of many epochs, but we may change this depending on the data and the task at hand

Weights: "Importances" assigned to the signals being sent from one neuron to another in a neural network; Values that make up the actual "mapping" of a neural network from input to output, through hidden layers, and optimized through gradient descent across training epochs

Gradient Descent: A mathematical algorithm whereby neural networks attempt to find given weights to assign throughout the network that minimize the overall loss for a task; The attempted "descent" down the curve of a function to a convergent minimum

Weight Initialization: The strategy whereby weights are assigned in a neural network prior to any training; Usually done randomly, but sometimes other strategies are used

IBM Watson Studio: IBM's cloud-based Integrated Development Environment (IDE) for Data Science and AI

Python: A high-level, general-purpose programming language preferred by many Data Scientists and AI Engineers because of its associated libraries

TensorFlow: A free and open-source Python library developed by Google primarily focused on Deep Learning; Preferred by many Data Scientists and AI Engineers for building neural networks

Keras: A free and open-source Python library developed by Google engineer François Chollet that provides an easier-to-use interface for programming with TensorFlow

5.1 Where to Go Next

If you're interested in looking closer at Deep Learning and neural networks, such as into the mathematics weight calculation, optimization through various forms of gradient descent, and how all of this can change in different types of neural networks (different "architectures"), we encourage you to take a look at course five of IBM's Machine Learning Professional Certificate on Coursera.

Here are a few more consolidated resources on the topics we've discussed in this lab that you can find on IBM's developer community:

- Watson Studio
- AI Beginner's Guide
- Neural Networks
- Deep Learning
- Gradient Descent

5.2 Stay in Touch

Thank you for attending this lab! It's been a pleasure having you. Regardless of your background in AI, Data Science, and programming, we hope you've retained some useful insights that you can go on to apply to your own organization.

If you have questions, feedback, or simply want to chat more about Data Science and AI after the session, don't hesitate to reach out to Alex (alexamari@ibm.com) and/or Cedric (cedric.jouan@ibm.com).

Also consider joining IBM's Global Developer Community for more on the latest Data Science and AI products and insights from IBM