

PEAK OF FLIGHT

NEWSLETTER

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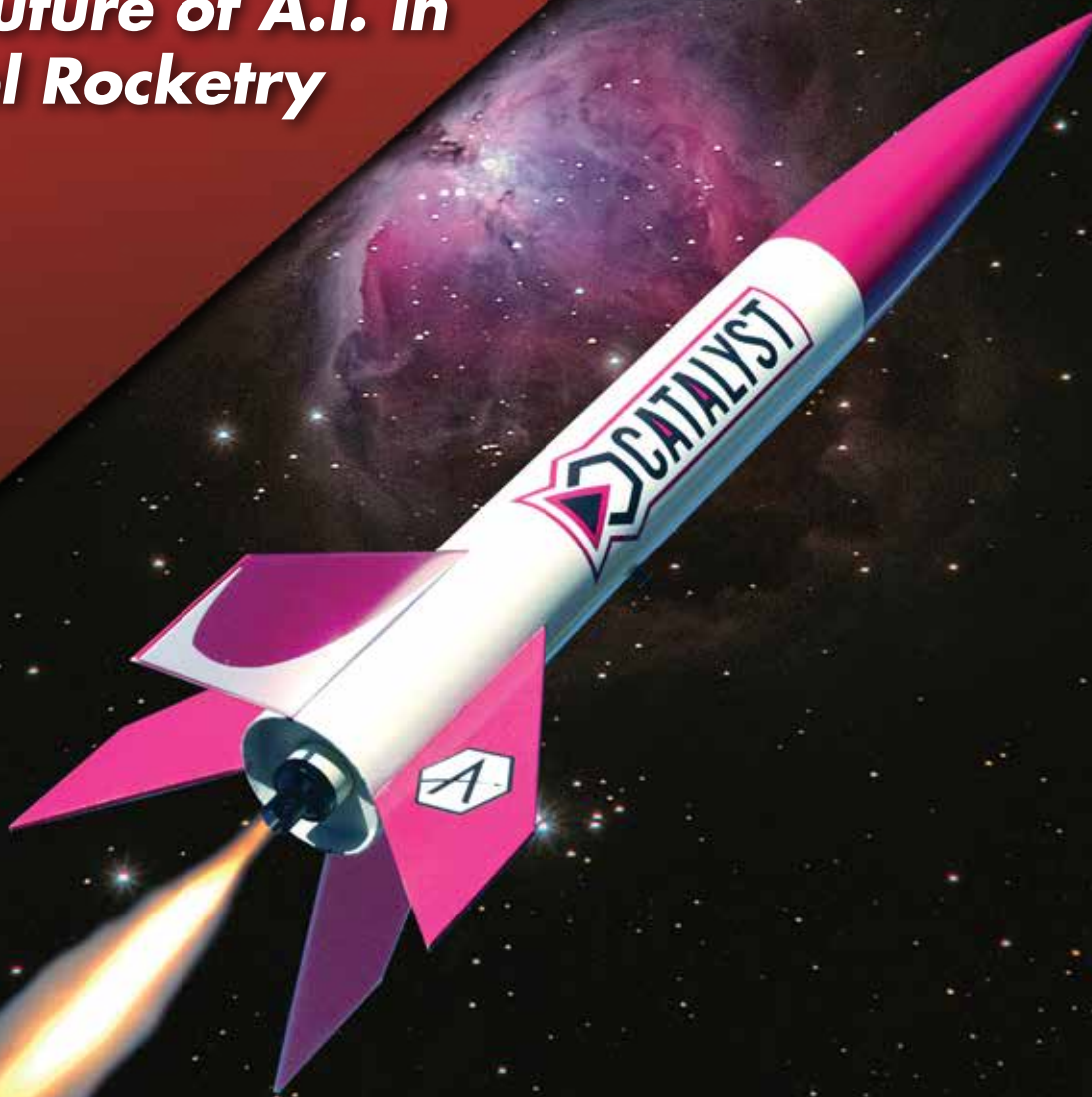
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In This Issue:

**The Future of A.I. in
Model Rocketry**



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The Future of A.I. in Model Rocketry

By Martin Jay McKee

Years ago, when I was completing my computer science degree, there were two sub-fields that I found particularly interesting. One of those was control systems. That makes sense, I have been interested in combining electronics with things that fly (airplanes, rockets, multi-copters, etc.) for a very long time and control systems are vital to making that work. The other area that caught my interest was AI. More than a decade later, AI burst into the public consciousness again with the release of projects such as ChatGPT and DALL-E which took refined versions of the same algorithms and processes that have been studied for years and combined them with the massive processing power of modern computers and GPUs (General-Purpose Graphics Processing Units) – that is, graphics cards – to produce systems that are able to do incredible tasks. The flash and hype of AI in the media, however, might go a long way to obscuring the breadth of AI techniques and the depth to which they are already used in a variety of industries. As happened with the transistor over the past several decades, what was once a headline has become a part no more interesting than a brick or mortar. But, of course, the materials to construct a house (or build electronics) are still crucial to us being able to produce those things no matter how uninteresting the components become. It makes sense, therefore, to examine not just the flashy parts of AI but the boring parts as well if we are to consider how they might be used in model rocketry.

Model rocketry began as a hobby on the cutting edge of science and engineering. With the coming of the space race and the atomic age, the late 50s and early 60s were filled with an optimism and futurism that combined with the very public NASA missions. This drove an interest in all things space related. To some extent or other, this connection with cutting-edge technology has remained a part of the hobby since that time. With the advances in motors from zinc/sulfur, to black-powder, to composites and hybrids, the propulsion advances have kept pace

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with technology. Similarly, the electronic payloads have grown immensely in capabilities over the past couple of decades. And design software has done the same.

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The Future of A.I. in Model Rocketry

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The question, therefore, must be asked, “what is the next big revolution for the hobby of model rocketry?” In this article, I am not seeking to answer this question, but rather to explore one avenue of possibilities, the ever present specter of artificial intelligence.

With any technology that seems to be fueled by hype it is easy to feel that it is simply an over-blown fad that has little value in and of itself. I, in fact, despite my interest in it, have often found myself disappointed by the results of AI when compared to the apparent promise. That is not always the case with new technologies. When the transistor was invented at Bell Labs, no one could guess how ubiquitous and important transistors would become. Indeed, between



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cell-phones, our cars, computers, and appliances, we each interact and depend directly upon billions of transistors daily. The wider world around us is dependent upon trillions more. By contrast, chat-bots like ChatGPT make a very small impact on our actual lives. Much of that impact, in fact, might be considered negative as simple ChatGPT-like systems are at the core of the robo-call systems that we all hate so much when we must call a company for technical support, or to schedule an appointment, or buy tickets... or a thousand other things. However, despite the current hype, AI in one form or another has been around for decades and

it has not revolutionized the world in the way that many are expecting; it has, however, revolutionized the world in important - if invisible - ways. As such, we must be cautious going forward.

I am going to be examining a few possible applications of AI to teams competing in the American Rocketry Challenge. I chose this target rather than the “average” model rocketry hobbyist (if there even is such a thing) because a competition of this sort makes the desired goal very clear. Unless a hobbyist is interested primarily in similar competitions or record attempts, the “goal” of the hobby is substantially more nebulous and that would make our exploration even more hazy. Before digging into the applications of AI, however, we will look into what is meant by artificial intelligence and provide a quick “30,000 ft” overview of different AI technologies. Throughout this article I have included references to only a small sampling of the vast literature on the subject. The interested reader is encouraged to explore further as an article such as this could never give a complete picture of the possibilities, difficulties, or challenges.

What is AI?

While it would be nice to be able to nail down a simple, understandable, one-line definition of artificial intelligence, the truth is that AI is a sprawling field of study that takes research from computer science, linguistics, numerical optimization, and statistics and attempts to meld them into systems to solve problems that range from as simple as controlling a light, to replicating human level intelligence - something that is generally termed Artificial General Intelligence (AGI). Still, we shall do our best to frame the different major ideas involved in a way that they can make some sense. According to ChatGPT (as seems appropriate for this article),

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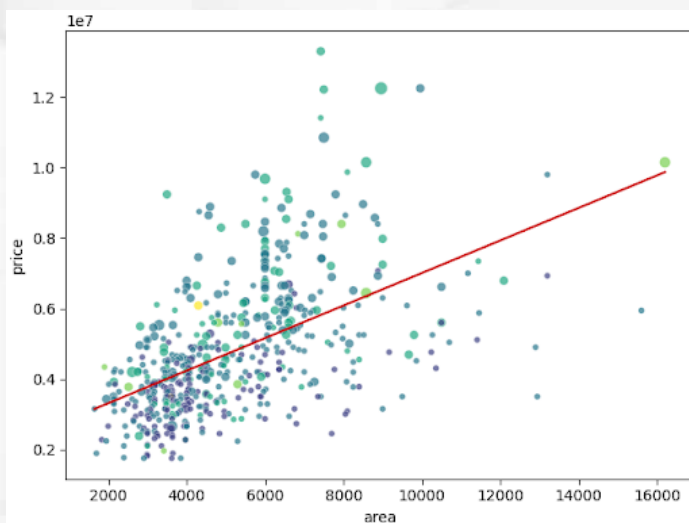
The Future of A.I. in Model Rocketry

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AI, or Artificial Intelligence, refers to the development of computer systems that can perform tasks that typically require human intelligence, such as learning from experience, problem-solving, and language understanding. It encompasses a wide range of techniques and technologies, including machine learning and deep learning, to enable machines to mimic cognitive functions and adapt to various situations, ultimately aiming to enhance efficiency, automate tasks, and improve decision-making processes.

This is a workable definition for the umbrella term AI. If we are being flippant, we could say that AI is an attempt to imitate some attribute of human intelligence. Under the umbrella there are many different approaches including statistical models, machine learning, neural networks (the smaller umbrella which contains deep learning), and many others. Before examining how these techniques might be applied to model rocketry, it's best that we have some understanding how they function.

The most basic (and oldest) of these approaches is statistical modeling. We see statistics all around us in science reporting, poll results, and even in random conversations. The field of statistics is fundamental to our day-to-day life. This is likely part of the reason why it is generally forgotten when discussing AI. Frankly, it's boring compared to the intriguing deep learning and large language models. Those more advanced techniques, however, still depend in a fundamental way on statistics. Rather than descriptive statistics like mean and variance, AI depends upon predicting models where we can define a statistical model as a *mathematical model conditioned on specific statistical assumptions and that is used for the generation of sample data or to make predictions*. A very simple form of statistical model is a linear regression



With the total area of the house along the x-axis and the price along the y-axis, this graph shows that while there is a correlation between area and price, there seem to be other variables which are important as well. The data presented here were taken from [7].

model. A typical example might be estimating house prices from square footage. The graph of housing prices shows a couple of interesting features. First, it shows that the best fit line (in red) isn't all that good. There's tons of scatter away from the line. This makes sense because the value of a house isn't based solely on its size. The graph shows a couple of other features that could make it more or less valuable with the size of each point based on the number of bathrooms (the large points are clearly toward the top on average) and the color of the point based on the number of bedrooms (with the number increasing from blue through green to yellow). Linear regression can be done in any number of dimensions to capture the effects of these other related variables.

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Another highly useful method is numerical optimization. Put simply, optimization is a process by which the “best” set of parameters are chosen to reach a defined goal. When doing mathematical optimization, this goal is specified by a cost function that is then minimized (or maximized) by adjusting the parameters of the system. Fairly traditional uses of numerical optimization in model rocketry are finding the maximum altitude mass of a rocket (because depending upon drag a heavier rocket is sometimes best), and “backing out the Cd (Coefficient of Drag)”. In both of these examples, many simulation runs are required to find the desired value. A numerical optimization solution can be used to find a minimum value, a maximum value (such as the maximum altitude mass) or to get as near to a known value as possible (such as backing out the Cd). The techniques used for this optimization can run the gamut from a brute-force approach where the simulation is run with many different parameter values evenly spaced and the best result is chosen to extremely sophisticated algorithms which use information about the behavior of the cost function to direct the search. As simple as it is, a brute force method can be made to work as accurately as we might wish, but it can be extremely computationally expensive. With just a single parameter we wish to estimate, it’s not too bad. For instance, if we know that the Cd (coefficient of drag) of a rocket is between 0.5 and 1.0, we can estimate to better than 1% by simulating 100 times (with Cd separated by 0.05) and choosing the flight closest to the measured altitude. At about 1/10th of a second per simulation, the optimization would take only 10 seconds which is not immediate, but it certainly is not unusable. On the other hand, if it is desired to estimate mass and Cd to the same 1% each, the number of simulations needed

increases to $100 \times 100 = 10000$, which would lead to an optimization run of approximately 15 minutes. This is well more than most people would be willing to sit down for. And, to add insult to injury, that also disregards the fact that just as in the linear regression example we saw before with housing prices, there are likely to be confounding variables that will have to be understood for any answer to mean anything.

To solve the problem of excessive run times, more advanced techniques have been developed which make optimization more efficient. The simplest of these methods is gradient descent. After each run, the parameters are moved slightly in the direction that seems to be leading to the more optimal solution. Gradient descent is a generally simple method but it requires us to know (or be able to estimate) the best way to change the parameters to optimize our cost function. This direction is known as the gradient, hence the name of the technique. Sometimes determining this directional change is easy, but often it is actually pretty difficult. That has led to other techniques such as genetic algorithms and simulated annealing which actually do a stochastic exploration of the parameter space. A number of tests are made and then more tests are made in the area around the best seen thus far. There’s lots of details that we’re flying right past in this introduction, but these sorts of methods are great when a system is very difficult to predict but fairly easy to check (as is often the case with the aerodynamics of systems). Numerical optimization may not seem to fit quite into the AI camp, but every single advanced AI algorithm uses numerical optimization all over the place internally, and optimization can be used to good effect by itself as well.

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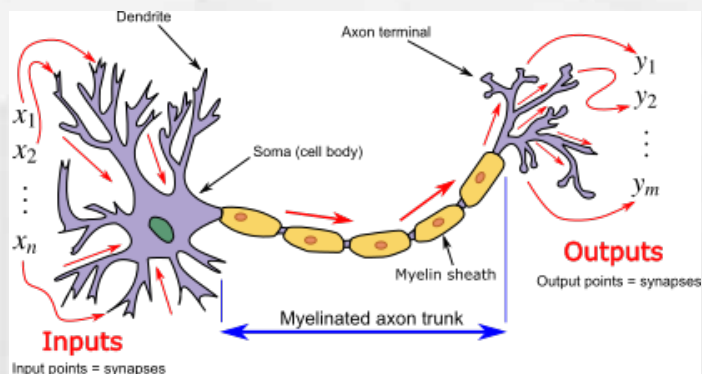
Another primary method under the umbrella of AI is the wide variety of generic machine learning (ML) techniques. Machine learning *uses algorithms to make decisions or predictions based on data*. As the training data changes, the decisions and predictions change as well. This is what is meant by learning. Sometimes the “learning” is static. The data is collected, the system is trained, and the system is then used to make predictions. Sometimes, the training is “online,” that is, the data collection happens while the system is running. These online systems generally feel much more intelligent to us, however, they typically are less effective than one-time trained systems as it is possible to catch all the little issues in the training right at the beginning. As an overview of some of the ML methods not otherwise covered in this introduction, we’ll take a look at clustering and classification.

Clustering is a machine learning technique that breaks a set of values into related groups, or clusters. Depending upon the algorithm, clustering can be achieved with a fixed number of clusters (say three) or the algorithm can also determine an optimal (again for some goal) number of clusters. Clustering is primarily useful for understanding the structure of data. Once clusters are constructed, however, they can be used to train an ML algorithm to do a variety of other tasks, including classification.

Classification is the process of identifying a group that a sample belongs to. A prototypical example of classification is image identification and there are as many different techniques as there are applications. Some techniques are really just a form of a clustering algorithm with a fixed number of classes, or a variation of regression known as Logistic Regression which allows for determining a binary value (yes/no) for inclusion or exclusion from a group.

Classification algorithms then increase in complexity all the way up to the most complicated neural network architectures. There have been many uses of image classification over the years. Very rudimentary OCR (Optical Character Recognition) systems have been used by the USPS (United States Postal Service) since the mid 1960s. These have included classification systems to allow for automated processing of letters since the 1980s. Other uses of classification include things like medical systems to help with diagnosis, fault detection systems to warn products of unsafe conditions, and automated accept/reject systems as might be used for insurance claims or job applications.

What we have discussed so far, while fully within the camp of AI, is generally not what people think of when they hear the word. Much of the talk about AI these days centers around deep learning, a technique that is based around



Artificial neural networks were loosely based on the arrangement and function of biological neurons where the Soma (the body of the cell) is replaced by an activation function and the Synapses are replaced with weights. Some older designs take the analogy even further, but those designs are less used these days.



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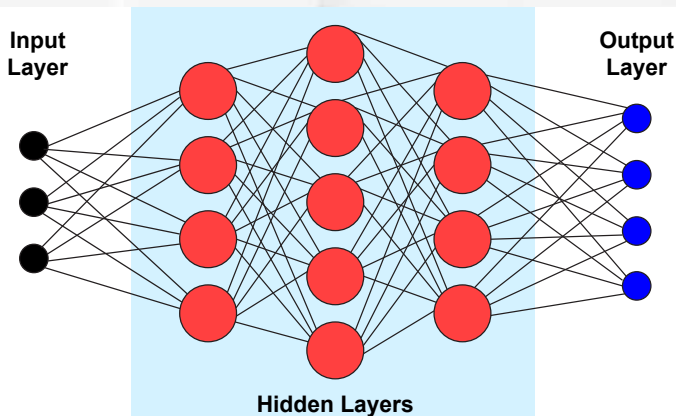
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neural networks. The theory of neural networks goes back nearly as far as computers with the first work being done in the early 1940s on the Perceptron architecture. A neural network is a computational system that is modeled on the structure of a brain. There are neurons (which do the computation) as well as weights (or synapses) which represent the connections between neurons.

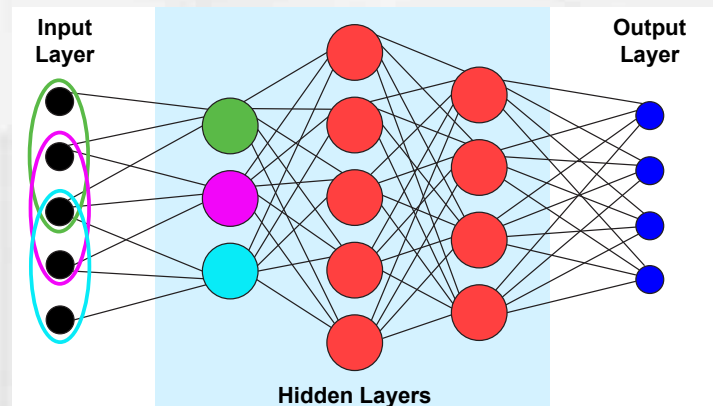
The structure of a neural network is that of a number of different neuron layers that are connected, generally straight through from the input to the output by weighted connections (similar to synapses in a biological brain). A network that has a later layer connected back to an earlier layer is called recurrent. These recurrent networks are

used for processing sequences (such as words, sounds, or data over time) though not as often as they were in the past, due to difficulties with training them. Generally, each neuron in a layer is connected to each neuron in the next layer. This is called a fully-connected layer and provides the most flexibility for the system to learn; but it can easily lead to difficulties because the network is too unconstrained.

Learning in a network often uses a method known as backpropagation learning which uses some very simple calculus (specifically, a version of the chain rule) combined with some type of numerical optimization as discussed earlier. Each time a new example is presented to the network, the learning algorithm calculates an error between the desired output and the computed output. This error is then used to adjust the values of each of



The input and output layers of a neural network are the only ones that are accessible outside the system so the remainder are termed "hidden" layers. A neural network can include any number of hidden layers with any arrangement of connections between the layers. If the connections only ever flow from the input toward the output, the network is a feed forward design. However, if any connection flows back toward the input (or an earlier layer) it is a recurrent network.



Each neuron in a convolutional layer only receives information from a portion of the previous layer. In so doing, the network is able to learn similar mappings across multiple areas. This makes Convolutional Neural Networks ideal for identifying features at varying scales and in different locations.

Vapor

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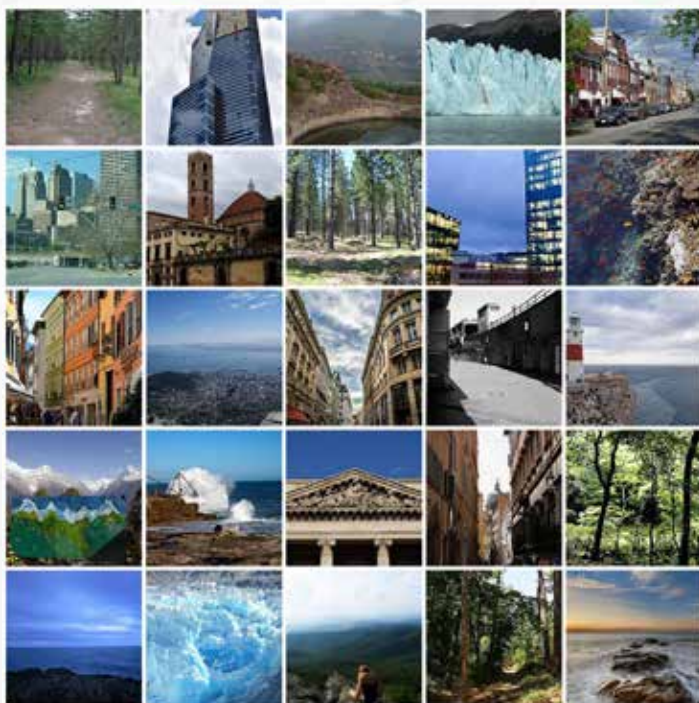
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These are a small selection of image examples from the Intel Image Classification Dataset [8] which are the sort of image typically used to train Convolutional Neural Networks to classify images.

the weights so that the network is more able to reproduce the expected values. By repeatedly applying this training to a large number of examples, the network learns to accurately reproduce the desired mapping.

Such fully-connected networks are useful for many tasks but they often struggle when faced with things like rotated or scaled images. For instance, a network might be able to detect a dog in the upper left corner of an image but if the same dog is made twice as large (or

half the size), or if it is moved to the lower right corner of the image, the network may not be able to detect the exact same dog. One highly effective solution to this problem—which has led to a great deal of the current AI renaissance—is the so called Convolutional Neural Network architecture. Convolutional networks do not use fully-connected layers but, rather, use many similar and overlapping views of the previous layer. Generally convolutional networks are used with multi-dimensional data like images, but they can be easily understood by taking a simple linear layer as represented in our illustration. Given an input layer with five neurons, and a field of three neurons, a second layer with three neurons could be created with an overlap of two. When properly trained the result is that each of the convolutional neurons then learn to identify similar features in each of the three fields. Maybe each of the neurons in the layer are tuned to detect the presence of a dog ear. Subsequent layers then learn to detect multiple ears close together, eyes, tongues, etc. And, as the layers are composed of neurons that only have access to a limited field of the previous layer, the network as a whole learns to identify features in any part of the image, with any rotation, and with any scale. The result is a network that can be trained to detect a dog in an image no matter where it is or how it is rotated. This can also be used for non-image inputs. For instance, the inputs to language systems are often based on convolutional networks.

One more highly useful network architecture (used in things such as Dall-E) is the Generative Adversarial Network (GAN). A GAN is not a unique architecture by itself but a purposeful combination of two (or sometimes more) networks. One network is trained to



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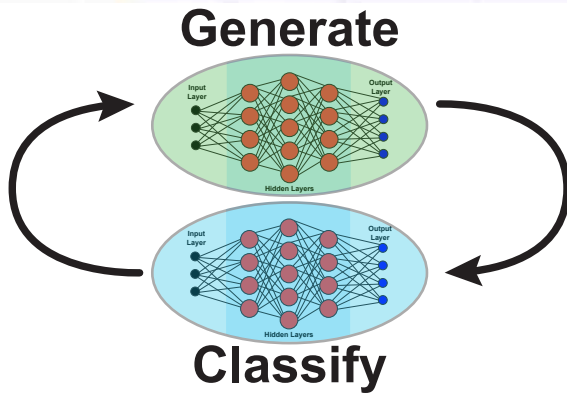
8

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The basic architecture of a Generative Adversarial Network is for the output of a generating network to flow into the input of a classifying network and for the classification to be used, in turn, to train the generator network to be more successful.

generate an output that matches the training data (say, pictures of cats). At the same time, a second network is trained to identify real pictures of cats. The networks are termed adversarial because when the generative network creates a picture, the second network attempts to determine if the picture is genuine or faked. The success or failure of the two networks is then used as a signal to improve the accuracy of the opposing network. GANs are not only used by systems such as Dall-E (basically a visual version of ChatGPT) but have also been used in many other - more serious, perhaps - applications including the prediction of fluid flow pressure distributions [4], and efficient optimization of airfoil shapes [1].

At the very bleeding edge of neural network technology are deep neural networks. A deep network has dozens

or hundreds of hidden neuron layers rather than just a handful. The advantage of doing this is that each additional layer makes the network able to model much more complicated functions. This “high-tech” solution actually seems pretty simple - just make it bigger! But, training a deep learning model is mathematically difficult and computationally expensive. There have been a number of advancements that have worked out the math to make training possible and the availability of data centers with hundreds or thousands of GPUs (graphics processing units) to run the code on have taken care of the computational problems. Because the truly large neural network models require such extensive processing capabilities however, they are unlikely to ever become part of our day-to-day rocketry hobby experience at home... unless made available by a vendor capable of renting the computer capabilities.

Finally, we find ourselves at the foot of ChatGPT which is in the class of Large Language Models (LLMs). These AI systems are typically a combination of many techniques but are, generally, based on one or more deep neural networks. ChatGPT, for instance, is based on the Transformer architecture [10]. A convolutional network might form the input section of the system (to help deal with some of the weird variable word ordering of languages), while the output might be created by a recurrent version of a GAN. This is not the time to delve (any further than we’ve already done) into the functionality or design of AI systems but rather to transition to talking about how they might be used in our peculiar niche of model rocketry.

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Use in Model Rocketry

To motivate some of the potential uses of AI in model rocketry, let us consider how students might benefit from AI systems assisting them in the design, testing, and analysis of a rocket built to the specifications of the 2022 American Rocketry Challenge (ARC)[9]. While the specific rules are detailed in the included figures, what concerns us most particularly here is the fact that the ARC is a competition that requires teams to come as close to a target altitude and stay aloft as near to a target duration as possible while meeting rocket design constraints such as tubes used, maximum weight, and motor limitations; all while carrying the payload of a raw egg. In the 2022 season (as outlined in the constraints figure), the rocket was required to be a minimum of 650 mm long, weigh no more than 650 g, and use two different tube diameters. The specific targets and scoring for the 2022 season are reproduced in the scoring figure.

Rocket Constraints:

- Weight ≤ 650 g
- Length ≥ 650 mm
- Tubes of two different diameters (150 mm minimum length)
- Payload (one large egg) in one tube, engine in the other
- Total impulse ≤ 80 Ns

These are the general constraints as specified in the 2022 American Rocketry Challenge rules.

Flight Scoring:

- Qualification
 - Duration Score
 - $41 \leq t \leq 44 \rightarrow 0$
 - $T < 41 \rightarrow 4 * (41 - t)$
 - $T > 44 \rightarrow 4 * (t - 44)$
 - Altitude Score
 - $\text{abs}(835 - h)$
- Finals
 - Targets by coin flip
 - 810 ft and 40-43s or,
 - 860 ft and 42-45s
 - Duration Score
 - $t_{\min} \leq t \leq t_{\max} \rightarrow 0$
 - $t < t_{\min} \rightarrow 4 * (t_{\min} - t)$
 - $t > t_{\max} \rightarrow 4 * (t - t_{\max})$
 - Altitude Score
 - $\text{abs}(h_{\text{tgt}} - h)$

This is an outline of the scoring specified in the 2022 American Rocketry Challenge rules. More than anything, this is included to make it clear that there is actually interesting structure to the rules of the challenge and that designing a rocket to be successful requires more than just designing for maximum performance.

There are a number of unique challenges with ARC. To begin with, while many teams are active over many years, it is a competition that tries hard to be approachable by complete beginners. As such, part of the development of the rocket is the students learning about rocket flight,



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design and construction. The best mentors will, of course, be well versed in these skills, but not all teachers are and, as such, it would be a boon for teams in such schools to provide a system that can do real-time training. Moreover, because predictability and consistency are so important to success in ARC, the ability to detect faults in designs and flight systems (in real-time or post-flight) could be extremely useful. Another issue is that any data recorded from a flight can be analyzed to provide information about what modifications can be made to the rocket to target specific altitude and duration targets. Finally, the vast design space (based on different materials, geometries, engine configurations, ballast weights, etc.) makes both exploring the range of options and deciding on a “best” design difficult. These are tasks which can be automated. So, moving forward we shall keep the challenges of ARC in mind and ask the question of if some methods of AI used in full-scale aerospace engineering can also be used by teams in the American Rocketry Challenge to improve their performance and consistency.

Potential for AI Help Systems

One thing that can be missing for some students beginning their journey's in the ARC is a mentor that has substantial subject knowledge in the construction of model rockets as well as the physics, aerodynamics, and structural mechanics of rocket design. They may also be lacking skill and experience in using the related design software such as [RockSim](#). Between forum posts, YouTube videos, and random documents scattered around the internet, all the information that one could desire to learn about these things are available. However, one needs to know what they are looking for. And, when you're just starting to learn something, sometimes you don't know the correct

questions to ask. Of all the potential places that AI could assist (especially beginning) modelers, however, this may be the most immediately available. I ran a quick test with ChatGPT. I asked the very basic question, “How can I make my model rocket go higher?” And received a generally well constructed answer that while far from advanced, certainly would be of assistance to a beginner.

Improving the altitude of your model rocket involves optimizing various factors such as design, materials, and launch conditions. Here are some tips to help you make your model rocket fly higher:

1. Aerodynamic Design:

- **Streamlined Body:** Ensure your rocket has a sleek, aerodynamic design to reduce air resistance. Use a pointed nose cone and smooth fins.
- **Fins:** Experiment with the size and shape of fins. Larger fins generally provide more stability, but they also increase drag. Finding the right balance is crucial.

2. Weight Reduction:

- **Minimize Weight:** Lighter rockets generally reach higher altitudes. Use lightweight materials for construction, such as balsa wood or lightweight plastics.
- **Payload:** Limit the weight of your payload. Excessive weight can significantly affect the rocket's performance.

3. Engine Selection:

- **Use a Higher-Power Engine:** Choose a rocket engine with more thrust. However, be cautious not to exceed the rocket's structural limits, as this could lead to instability or damage.



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11

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4. Launch Angle and Launch Pad:

- Optimal Launch Angle: Adjust the launch angle to optimize the trajectory for altitude. A launch angle of around 70 degrees is often recommended.
- Stable Launch Pad: Ensure your launch pad is stable and correctly aligned to prevent off-course flights.

5. Recovery System:

- Efficient Parachute: Use a properly sized and well-made parachute for the recovery system. It should deploy at the right altitude to allow a safe descent.

6. Aerodynamic Stability:

- Center of Mass (CM) and Center of Pressure (CP): Ensure that the center of mass is ahead of the center of pressure for stability during flight. Adjust the positioning of the fins and other components accordingly.

7. Streamlining the Launch Rod:

- Smooth Launch Rod: Ensure the launch rod is smooth and free from any imperfections. A smooth launch surface reduces drag during liftoff.

8. Wind Conditions:

- Choose Calm Days: Launch your rocket on days with minimal wind to prevent wind resistance from affecting the trajectory.

9. Test and Experiment:

- Iterative Testing: Experiment with different configurations and gradually make changes based on your observations. Keep a log of your launches and adjust your design accordingly.

10. Legal and Safety Considerations:

- Comply with Local Regulations: Ensure that you are complying with any local regulations regarding model rocketry. Safety should always be a top priority.

Remember to follow safety guidelines and regulations when launching model rockets, and consider joining a local rocketry club for additional guidance and support.

This is absolutely not a perfect response to the question. For instance, section 2 makes the claim that reducing the weight of a rocket will "generally" lead to higher flights. This is strictly correct but as is implied by the earlier discussion of an optimal mass, this is not always the case. If maximum altitude is the goal, that answer is misleading if not actually wrong. Moreover, the phrasing of 8 implies that wind resistance is something that happens on windy days. While wind resistance (drag) happens on every flight, it is certainly true that wind can affect a rocket's trajectory. Indeed, there is the potential for wind to cause lower flights but - in the worst of situations - even unstable and unsafe flights. There is little to take issue with in ChatGPT's response. Most complaints are purely pedantic.

ChatGPT was trained on a selection of random content from all over the internet. It has not had any extensive training in model rocketry or aerodynamics, yet it did pretty well. Of course, it also requires (as mentioned earlier) a massive computer system to respond quickly. What if a similar system (though smaller) was trained entirely on content appropriate to model rocketry? At Apogee Components we have produced over 600 newsletters, 400 advanced construction videos, and hundreds of extremely detailed web pages describing rocketry related products. Using even just that for training of a LLM (large language model) to be used as a conversational rocketry assistant (or rocketry help system) would easily lead to a system that was much more capable than ChatGPT at the specific task of providing answers relevant to all aspects of rocketry while still making the language model small enough to run on a standard computer.

1:21
SCALE
MODEL



X-15
ROCKET KIT

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While chatbots are certainly capable of providing wrong information sometimes, this is not the disadvantage it appears to be. In fact, the potential to be wrong is something that is inherent to how these systems work. Each response is constructed by considering the probabilities of words following one another. That said, even experts make mistakes. Learning to double-check information is always important. The occasional misdirection that is likely to result from an imperfect system is unfortunate but not likely to be a major barrier to the system being useful.

Even more exciting, however, is the potential to directly integrate such a system into a rocket design software where the chatbot is given access to the design itself, the simulations, and where it has direct ability to change the design in accordance with requests. This would not only assist students in discovering more about their rockets, it would also provide an entirely new way for more advanced users to interact with the software. A paper placed on the arXiv very recently (July 31, 2023) explored a similar issue when such advanced chatbots might be used to replace more traditional “recommender systems” such as those used by Netflix (to select shows to watch) or Amazon (to suggest new products)[5]. The paper discusses both the potential challenges with achieving a system that is fully functional as well as discussing potential concerns - which they term “the trade-off between helpfulness, honesty, [and] harmlessness” - and clarifies some of the privacy and accuracy concerns inherent to such a system.

Finding Faults without Blame

One of the most important components of a successful ARC team is the ability to analyze limited flight data in such a way as to make consistent predictions. Every team,

no matter the affluence of the school they come from, is going to be limited in the number of test flights they are able to make. Given the vast range of variables that go into the repeatability of flights - which might include environmental conditions, exact weight of the payload, variations in motor performance, etc. - it is difficult to collect enough data to have a statistically significant sample. This is a problem inherent in analysis of real-world systems and is a primary aspect of experimental design - the effort to ensure the minimum of independent variables in any one observation. The challenge is then to take these limited data and make predictions or design systems to actively control the rocket. These are two related, though separate, goals and we will discuss them separately.

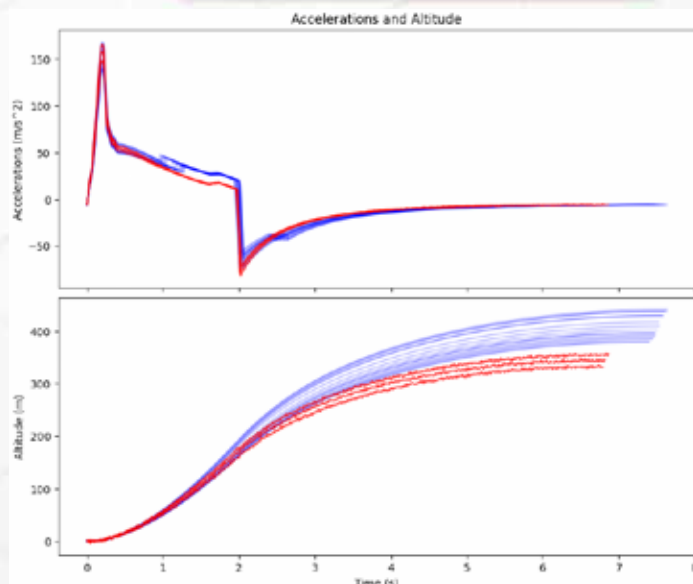
Typically an ARC team may simulate a rocket design with the final constructed weight to get as near as possible to the estimated peak altitude and flight duration. This is then checked against the measured altitude and flight duration and the simulation model will then be updated to more accurately match the observed flight characteristics. Given a sufficient number of flights and careful recording of things such as total launch weight, wind conditions, etc. - in combination with a robust rocket design - it is possible to achieve exceptionally repeatable results for the team. Every point in the process, however, is ripe for errors due to simple, human, mistakes.

By recording additional data, it becomes possible to more accurately identify where a flight deviates from the simulation. One approach to improving the adaptation of the simulation model would be to conduct all test flights with a flight computer that includes accelerometers



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This graph displays an example of the data that may be mined by an anomaly detection algorithm to identify areas of disagreement between flight data and simulation. In this case, the blue traces are simulation flights while the red traces are the measured flights. These data diverge due to a mismatch in the estimated and actual C_d and the actual flight also suffers from measurement noise.

(to detect acceleration), orientation tracking (using gyroscopes and magnetometers), and altitude tracking (using a barometric pressure sensor). This dataset could then be compared with a composite of multiple simulation runs using a fault (or anomaly) detection system to track where in the flight the simulation and real flight deviate most. This anomaly track allows for much more accurate updates of characteristics such as stability and coefficient of drag (C_d) curves. A similar system was outlined in an article by Deng, Cheng and Shi [6] where a combination of a GAN and a variation of a recurrent neural network

known as a Long Short-Term Memory (LSTM) was used to detect faults in a liquid fueled rocket engine in real-time. The advantage of the AI based solution is that the work of comparison is automated in such a way that much more in depth analysis can be completed in a much shorter time compared to methods that require more human feedback. That leads to the ability of a fault detection algorithm to identify (or even predict) a fault with substantially less variation from a nominal condition than might be expected for tracking one or two signals in a smaller dataset.

Continuing on from the idea of a post-flight analysis, similar AI techniques could also be applied to real-time control of the rocket's ascent and descent profile. While the ARC rules do prohibit the use of any pyro charges except those present in the commercial rocket engines, the rules specifically allow active control systems so long as they are autonomous (no radio control systems are allowed). These on-board control systems can actuate air brakes, parachute reefing, or other types of control to adjust climb rate or descent rate so that the rocket is most able to ensure the target values accurately and consistently. These sorts of controls can be implemented with traditional (non-AI) methods such as PID (Proportional-Integral-Derivative) control loops, but as many of them are not simple tracking or regulation controls and are, instead, decision systems which require predictions to be made, more modern control methodologies such as Model Predictive Control (MPC) are more appropriate. The use of AI in tuning these control systems as well as for processing the sensors in real-time to produce inputs for the control systems is a frontier that is only now being explored in advanced control systems research yet it is



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something that could - with only moderate difficulty - be made available to ARC teams and could, in the process, increase their ability to fly reliable altitudes and times.

A Design Assistant

A final system that could be implemented to assist ARC teams is generative design tools for model rocketry. Generative design is an application of AI that is tasked with creating new designs which seek to most effectively meet a goal. These sorts of systems could be as simple as the optimization systems that some of the current rocket design software includes to optimize mass or fin span for maximum altitude while ensuring stability, or they could be as complex as designing the mechanical structure of 3D printed components (to maximize strength/weight ratio, for instance).

An article from late 2022 [11], showed an interesting combination of technologies by combining neural networks with Computational Fluid Dynamics (CFD) simulations to do generative design of rocket engine injectors. By combining high-fidelity simulations with the extrapolation and generalization abilities of neural networks such as in this study, it would be possible to do whole rocket design optimization and even initial design creation in such a way that all generated designs would, at least, be a good start for teams. It would vastly reduce the major failures early in the design process for inexperienced teams and would give more advanced teams a leg up on exploring more possibilities. Combined with the conversational help system discussed earlier, rocket design would become an interactive endeavor between the AI system and the team. Even more powerful would be a fully holistic system that also includes the analysis capabilities described in the last section. This would allow the generative design to become

truly iterative by directly folding recorded data into the design process in place of - or in addition to - simulations.

One could conceivably make the argument that a full-blown generative design system of this type would remove any creativity or expertise requirement from the ARC team members. This does indeed demand consideration from the standpoint of creating a viable set of rules for the competition year after year. If, however, the goals of the competition are inherently in conflict, it creates a competition that can be won using a number of different approaches. ARC already does this to some extent by requiring both a time and altitude target. In a maximum altitude competition, by contrast, the slimmest lightest rocket with the largest motor is all but guaranteed to win (barring any catastrophic failures, of course). With a sufficiently multi-variate scoring system, however, it is not possible to design the "perfect" rocket. So, it seems to me, that no amount of assistance from a generative design system will obviate the need for a creative and dedicated team if the rules are properly specified.

Thoughts for the Future

I have introduced only a small fraction of the AI techniques that have been developed to this point, and considered their use in only a handful of model rocketry related applications. Even with this limited view of the possibilities, however, it is clear that applying AI to model rocketry is (as with all technologies) likely to be a mixed bag. In 2021 (a year before ChatGPT's public release), a paper was presented at the *Conference on Fairness, Accountability, and Transparency* that questioned the ethics and value in creating ever larger LLMs. This paper - with the fantastic title of "On the Dangers of Stochastic Parrots: Can Language Models be Too Big?"



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[2] - was controversial in the AI industry for pointing out the extreme energy costs of training these large models and for pointing out the inequity in the costs associated with creating and running the systems. These are not answered questions and while model rocketry is a small industry compared to the Google and Amazon monoliths that the paper primarily considered it is not immune from having to consider these costs. Nevertheless, it is apparent that there are places where these systems could provide services that are otherwise unavailable. The challenge then is to minimize the unwanted costs while making the systems as widely available as possible.

A much more detailed and in depth examination of how AI and ML could be applied to the general Aerospace industry was compiled by Brunton et al. [3] and it identified many other applications that could, potentially, find their way into the model rocketry hobbyist's toolbox. Of note, however, is that all the applications that they highlighted - as well as those that we examined above - are directly dependent upon a substantial amount of data being available. Some of that data can be generated by the modeler through things like recording altimeters included on flights or running a series of simulations. Other data, however, is out of reach of the typical hobbyist at the moment. Some of that, such as computational fluid dynamics (CFD) results could potentially be incorporated into the software together with AI, while other data such as the educational content that Apogee has produced requires the efforts of people with domain knowledge.

AI is not now (and, in my view, never will be) a panacea. Like any technology, it provides massive possibilities as well as a sufficient number of stumbling blocks to stub our toes with. Also, just like any technology, it requires

knowledge to use effectively. In the case that such knowledge is combined with a well designed system, however, there is every reason to be hopeful that future model rocketry hobbyists and competition teams could use the benefits of statistics, numerical optimization, machine learning and more general AI to create far more advanced model rockets in shorter amounts of time and with greater overall safety.

So, given the challenges and possibilities, what are the next steps? In the end, that depends on the model rocketry community at large. Model rocket manufacturers and the various open source software projects which support model rocketry can begin integrating AI features at any time. That leaves one glaring question to be answered however, "what do hobbyists want?" Do you, as a model rocketeer, find the possibilities of generative design interesting? What about a conversational help system? Let us know! The whole purpose of this article was to provide context and then spur ideas for future development.

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Entry Level
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Martin has been designing and building rockets for as long as he can remember. After originally toying with the idea of pursuing a career in Aerospace Engineering, he did a double major in Computer Science and Fine Art then spent a decade working in K-12 math and science education. Martin has been at Apogee Components as the Product Designer since August of 2022



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