FUSION: ADVANCED STELLAR MODELING

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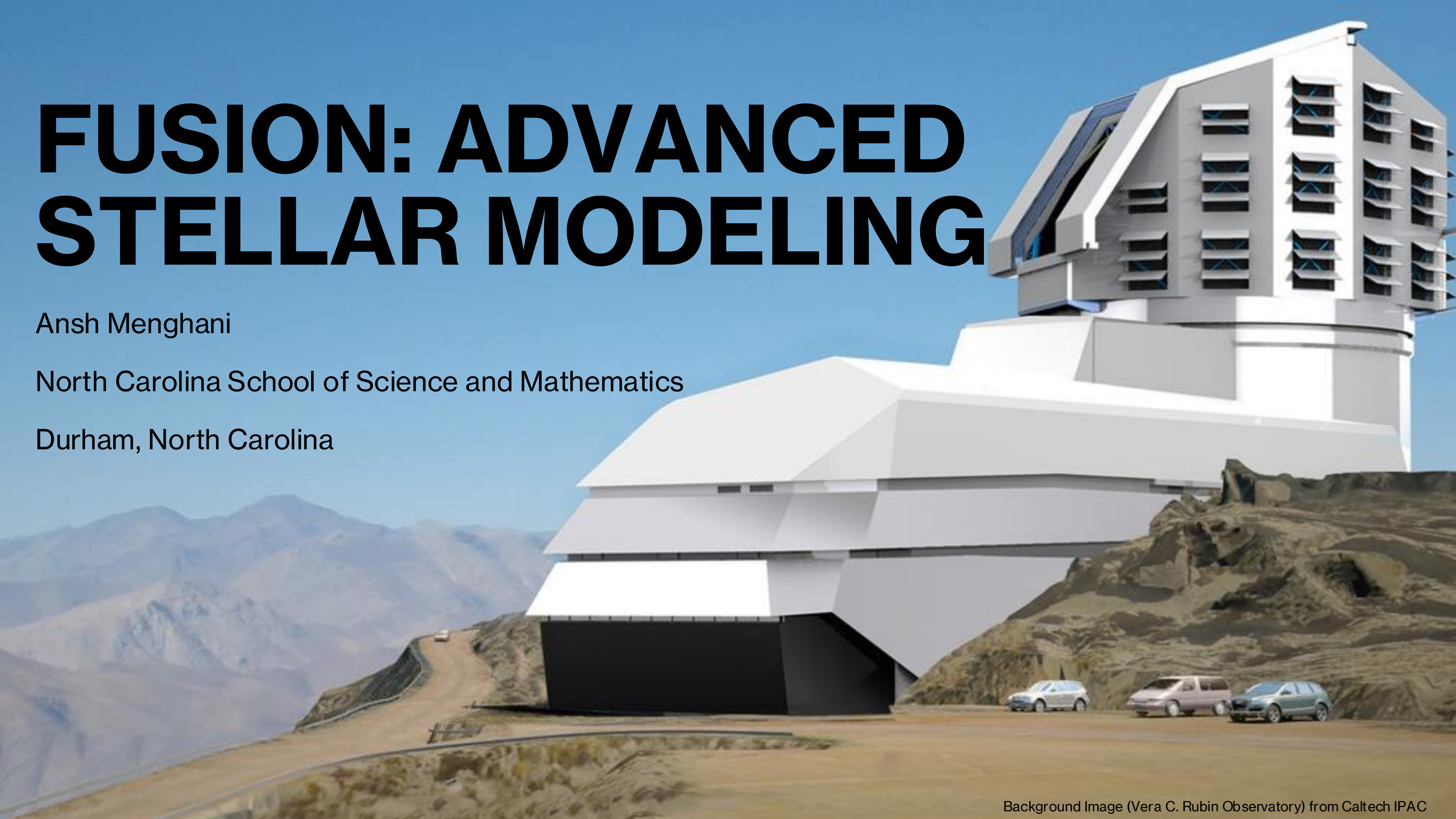

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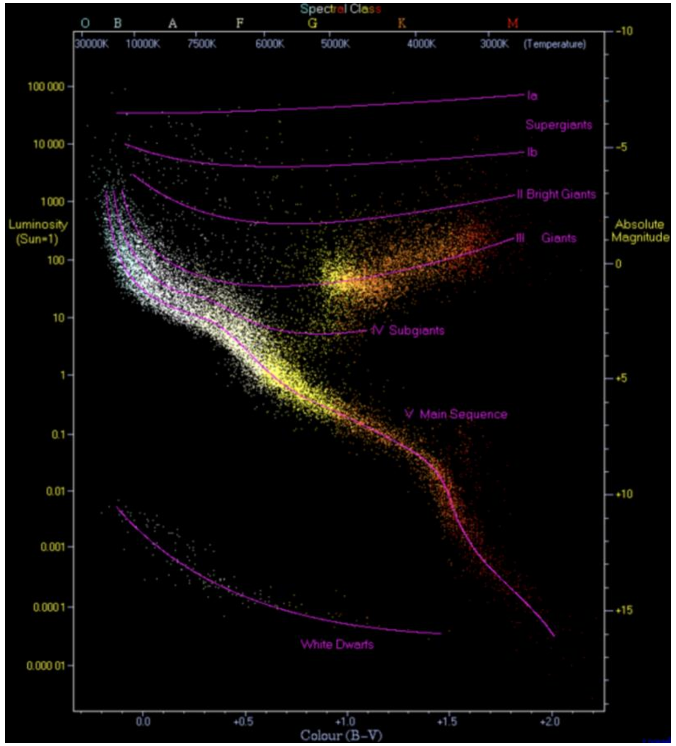
Introduction



A Hertzsprung-Russell diagram

Maximum Effective Temperature (°K)	Spectral Class
4000	M
5200	K
7000	G
20000	F
34000	A
42000	B
greater than 42000	O

Maximum Luminosity $(\frac{L}{L_\odot})$	Luminosity Class
0.1	D
25	V
100	IV
1300	III
8000	II
125000	Ib
greater than 125000	Ib

The Yerkes Classification system

Diagram by Richard Powell

Physics is all about **approximation**

Accurate predictions are especially hard in **astrophysics . . .**

. . . because of the way current mathematical and statistical models of stars work

Neural Networks can model the **complexity** of stars and model them **better** than traditional methods

This would allow for accurate and speedy models of stars to be made at a scientist's convenience

Neural Networks

A neural network is a type of regression **algorithm** that takes certain inputs and can make **predictions** based off those. It is **trained** on data.

It adjust its algorithm based on **how close** the prediction the model makes is to being **correct** (evaluated using a **loss**, or **error** function).

This is similar to a human brain **learning from mistakes**.

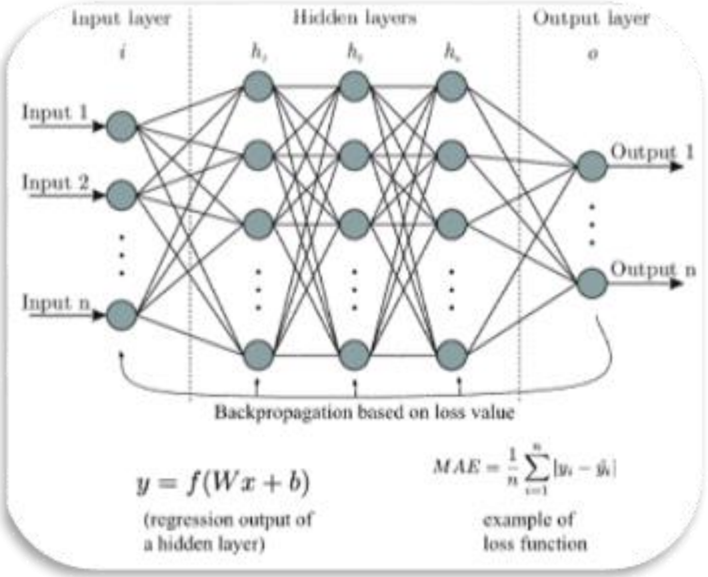
A Physics-Informed Neural Network **(PINN)** is a neural network designed to **respect** physics laws and formulas.

$$w_1 = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \end{bmatrix}, w_2 = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \end{bmatrix}, w_3 = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \end{bmatrix}$$

$$\begin{bmatrix} w_1 & w_2 & w_3 & w_4 \\ w_1 & w_2 & w_3 & w_4 \\ w_1 & w_2 & w_3 & w_4 \end{bmatrix} \text{ becomes } \begin{bmatrix} \leftarrow w_1^T \rightarrow \\ \leftarrow w_2^T \rightarrow \\ \leftarrow w_3^T \rightarrow \end{bmatrix}$$

Regression in neural networks is using linear algebra

Jordan, J. (2017, June 29)



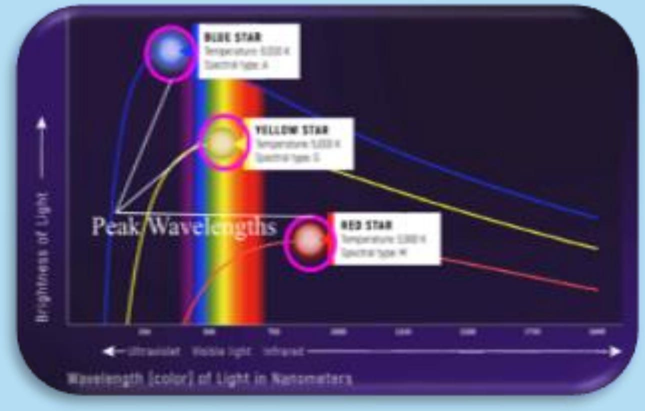
General structure of a Neural Network

Figure by Bre, F., Gimenez, J. M., & Fachinotti, V. D. (2018)

Stellar Parameters

- Stellar parameters are the attributes of a star (i.e., its luminosity).
- The "big three" stellar parameters are Effective (surface) Temperature, Luminosity, and Radius.
- These values are easiest to gain data on and are related by one formula: $L = 4\pi R^2 \sigma T^4$ where σ is the Stefan-Boltzmann constant.

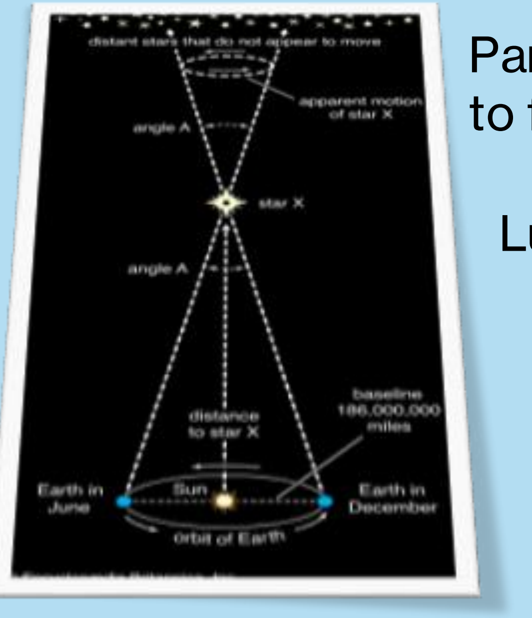
Finding the Effective Temperature:



Source: JWST, Public domain

$$\lambda_{max} = \frac{0.0029mK}{T}$$

Finding the Luminosity and Radius:



Encyclopedia Britannica

How parallax measurements work

Parallax Measurements to find distance

Luminosity Measurements

Source: NASA, Public domain

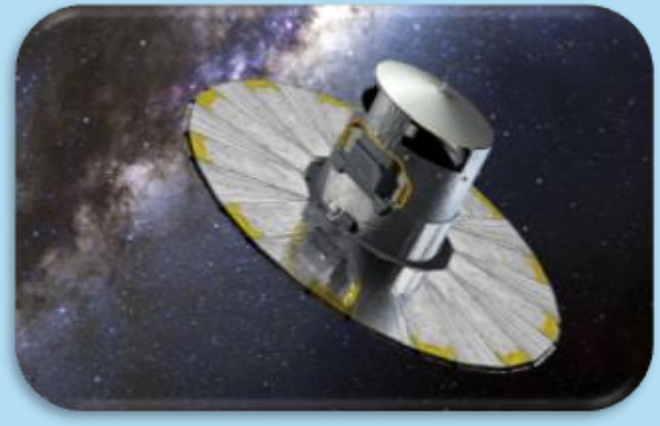
The Model

Goal

Develop a PINN that can **accurately model** many stellar parameters of any given star with **input values** of the star's effective temperature, luminosity, and radius.

Data Collection

15.5 million samples of data were selectively obtained and processed from the Gaia Data Release 3, collected by the Gaia spacecraft.



Gaia spacecraft
Image by ESA

The Model (continued)

Model Architecture

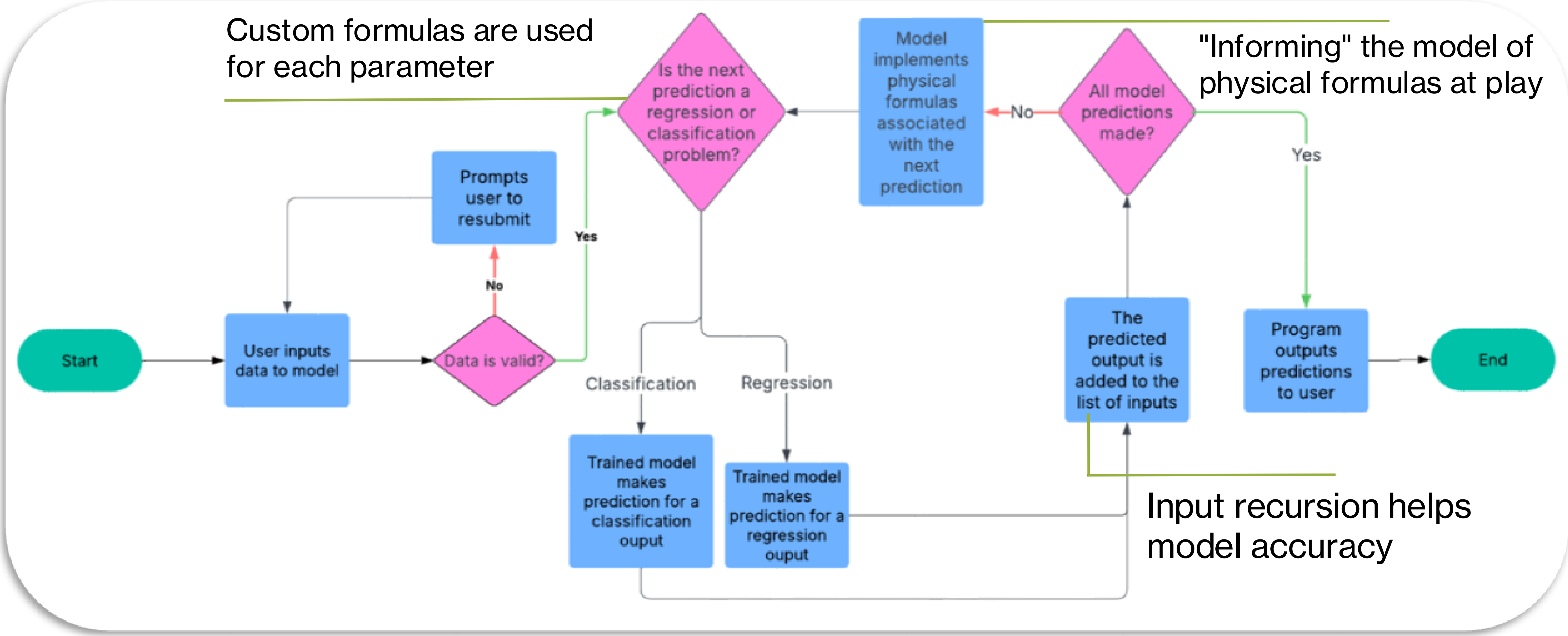
Outputs
- 5 parameters of star's dimensions
- 13 parameters describing the star
- 3 classifications of the star (spectral and luminosity classes and star type)

- **Custom** input **recursion**
- **Custom** validation loss **reward**
- Model is designed to **respect** physical formulas
- Other methods are implemented to **prevent** overfitting, **improve** classification performance, and **transform** each layers' outputs to the desired format
- The **best** model structure and data were found by **prototyping** and testing the model

Image by Julien Despois from hackernoon.com

Overfitting/Underfitting occurs when a model is too complex or too simple. A model will "memorize" training data when overfitted

Flowchart



Custom formulas are used for each parameter
Is the next prediction a regression or classification problem?
Model implements physical formulas associated with the next prediction
No
All model predictions made?
"Informing" the model of physical formulas at play
Yes
Prompts user to resubmit
Yes
No
Start
User inputs data to model
Data is valid?
Classification
Regression
Trained model makes prediction for a classification ouput
Trained model makes prediction for a regression ouput
The predicted output is added to the list of inputs
Program outputs predictions to user
End
Input recursion helps model accuracy

Accuracy and Speed on HR Diagram

The model was **iteratively** trained such that it trained and tested itself by looking at data many times.

Figure 1: Training loss

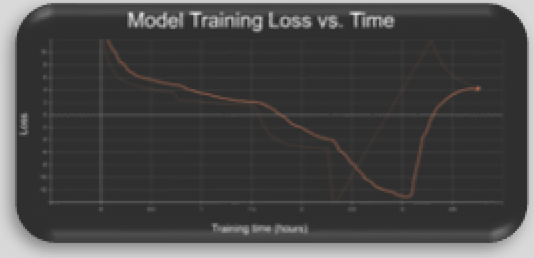


Figure 2: Validation Loss

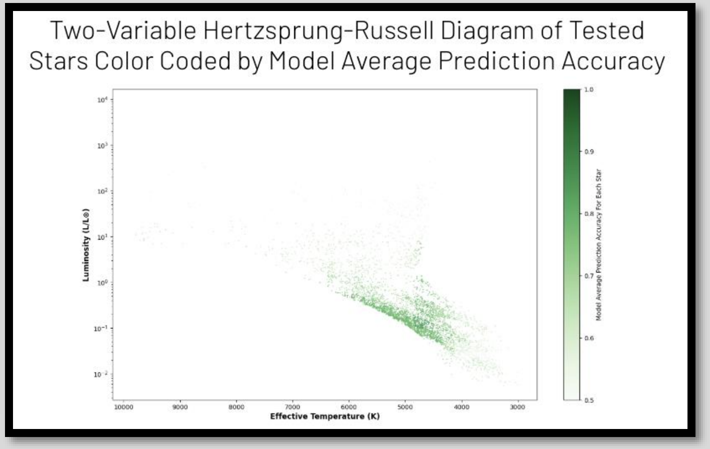


Figure 3: Model Accuracy Plotted on HR Diagram

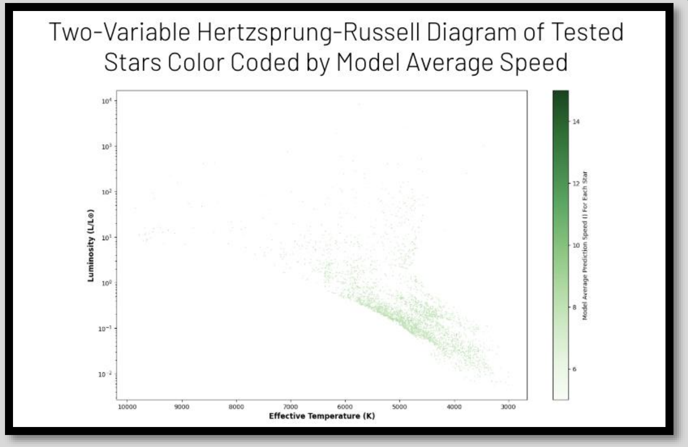


Figure 4: Model Speed Plotted on HR Diagram

Each datapoint is a **star** on the Hertzsprung-Russell diagram. The **darker** the dot, the **more** accuracy/speed the model exhibited when running predictions on this star.

Parameter-Based Model Evaluation

The model's accuracy by parameter predicted is shown on the left. Analysis of classification outputs is to the right.

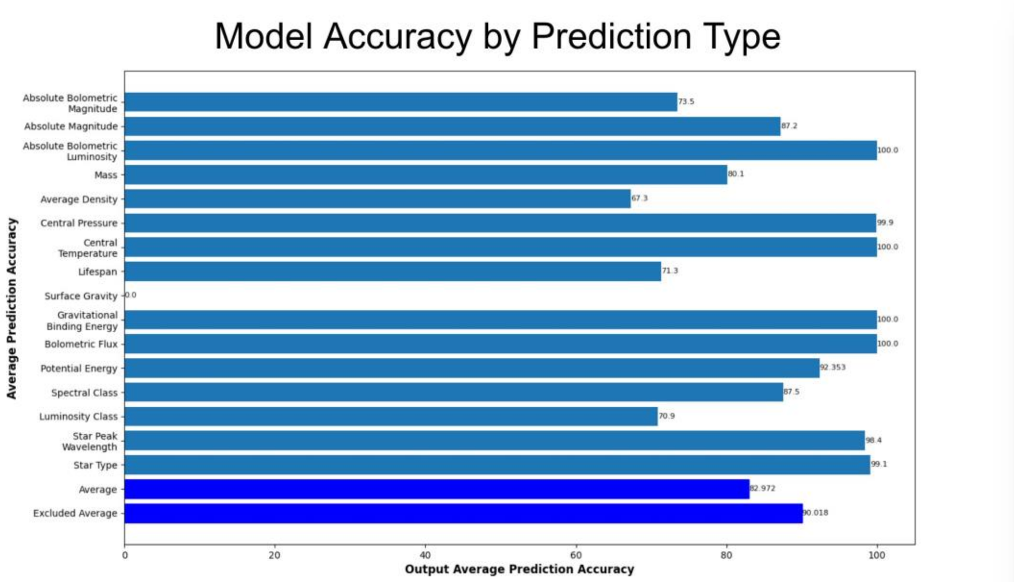
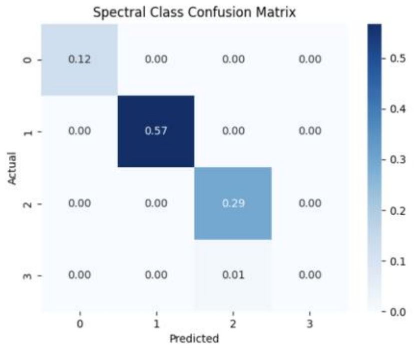
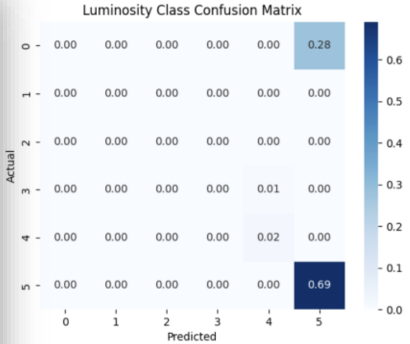


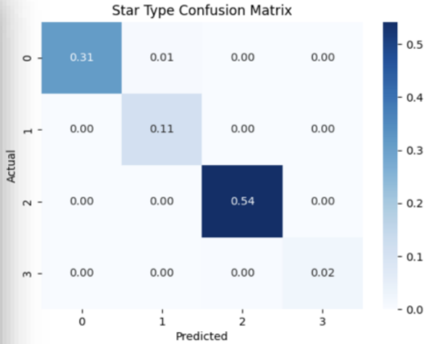
Figure 5: Accuracy of the model by parameter (±5%)



Accuracy Score	0.9860
Recall Score	0.9860
Precision Score	0.9726
F1 Score	0.9792



Accuracy Score	0.7112
Recall Score	0.7112
Precision Score	0.5058
F1 Score	0.5912



Accuracy Score	0.9870
Recall Score	0.9870
Precision Score	0.9873
F1 Score	0.9871

Figures 6, 7, and 8: Classification evaluation metrics.

Discussion

The model is attempting to obtain a loss and validation loss close to zero (figures 1 and 2), which indicates positive training behavior.

Refer to Figures 1 and 2

Loss and validation loss dip below zero due to the validation loss reward mentioned earlier. It is rewarding the model for improvements in validation loss by subtracting from the loss.

The model's performance is affected greatly by the star's effective temperature.

Main-sequence stars are modeled better than other types of stars such as:

Refer to Figures 3 and 4

- Stars that are not represented as much in the training dataset.
- Data-points/stars may be considered as outliers.

There is little to no variation of prediction speed.

Discussion (continued)

The low accuracy that is associated with very few parameters is likely due to how the model scales data.

Tiny errors can cause large accuracy gaps when values are small (e.g., 0.1 is close to 0.2 but a large percentage off).

Refer to Figure 5

The first nine outputs had four parameters with >85% accuracy, while the next seven only had one.

This means that the custom method used to recurse outputs into inputs (as described earlier) works!

Refer to Figure 5

Overall, classification scores were very good.

The low luminosity class scores could be because it was the only parameter with six possible outputs, while the other classification parameters had four each. This may have interfered with the model's algorithm.

Refer to Figures 6, 7, and 8

Final Model Accuracy:

90.018%

Average Prediction Speed:

8ms

Conclusions

Real-World Applications

- **Expands** machine learning and deep learning into physics.
- Can be used to **simulate** star systems that are very **hard to gather data on**
  - **First** stellar simulation model that does the job of **over sixteen models**.
  - The model has **better accuracy** and is **faster** than current models.
- This model can be used to **find previously unknown relations** between different stellar parameters.
- The machine learning techniques used in this model (specifically the custom ones) can be **replicated in other projects.**
- Simulations will help scientists **confirm** their observational results and help them easily **decide** what they want to use resources on to study.

Conclusions (continued)

Goals Met?

The goals described earlier have been met by the model! ☑

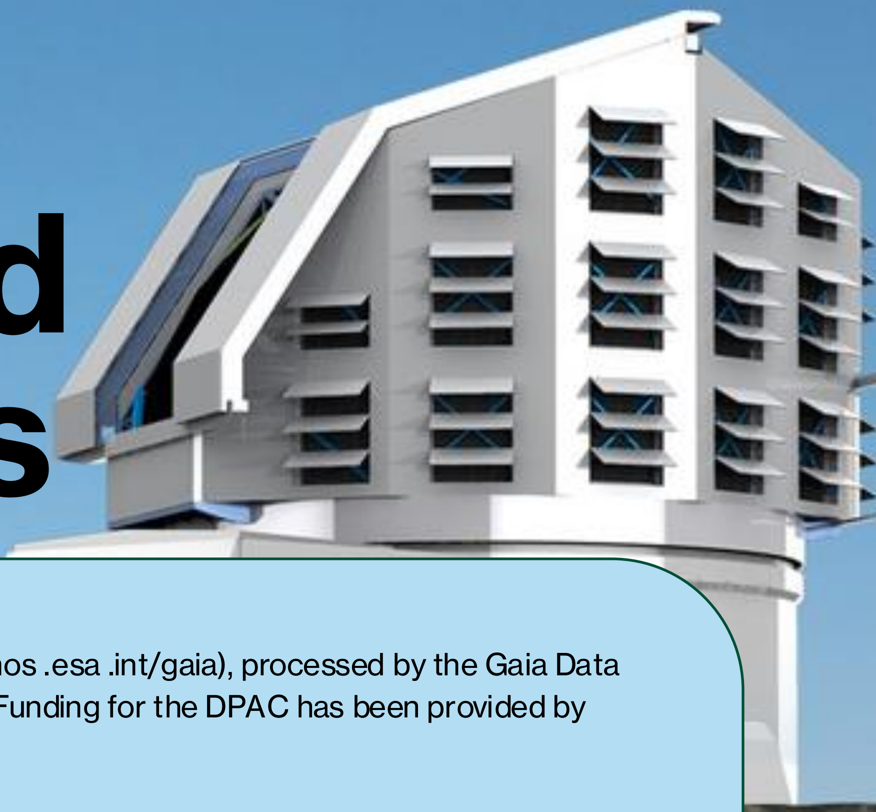
Possible Limitations

- Some parameters have a lower modeling accuracy than others
- The training dataset has less examples of rare stars

Future Goals

- Improve accuracy
- Gather more examples of rare stars

Key References and Acknowledgements



1. This work has made use of data from the European Space Agency (ESA) mission Gaia (https: //www .cosmos .esa .int/gaia), processed by the Gaia Data Processing and Analysis Consortium (DPAC, https: //www .cosmos .esa .int/web/gaia/ dpac/consortium). Funding for the DPAC has been provided by national institutions, in particular the institutions participating in the Gaia Multilateral Agreement.
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Thank You!
Any Questions?

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