

Virtual Mini Event, November 2021

#### Where is the Data?

Data Requirements and the Green School Bus Problem

Barclay R. Brown, Ph.D, ESEP Engineering Fellow Raytheon Missiles and Defense Barclay.brown@incose.net Ramakrishnan Raman, Ph.D, ESEP
Principal Systems Engineer

Honeywell ramakrishnan.raman@incose.net

#### Barclay R. Brown, Ph.D., ESEP



Barclay R. Brown is an Engineering Fellow at Raytheon Technologies, focused on MBSE and artificial intelligence and machine learning in systems engineering.

Before joining Raytheon, he was the Global Solution Executive for the Aerospace and Defense Industry at IBM, and lead systems engineer for some of IBM's largest development projects.

Dr. Brown holds a bachelor's degree in Electrical Engineering, master's degrees in Psychology and Business and a PhD in Industrial and Systems Engineering.

He has taught systems engineering and systems thinking at several universities and is a certified Expert Systems Engineering Professional (ESEP), certified Systems Engineering Quality Manager.



Barclay R. Brown, Engineering Fellow Barclay.R.Brown@ Raytheon.com



## Ramakrishnan Raman, PhD, ESEP

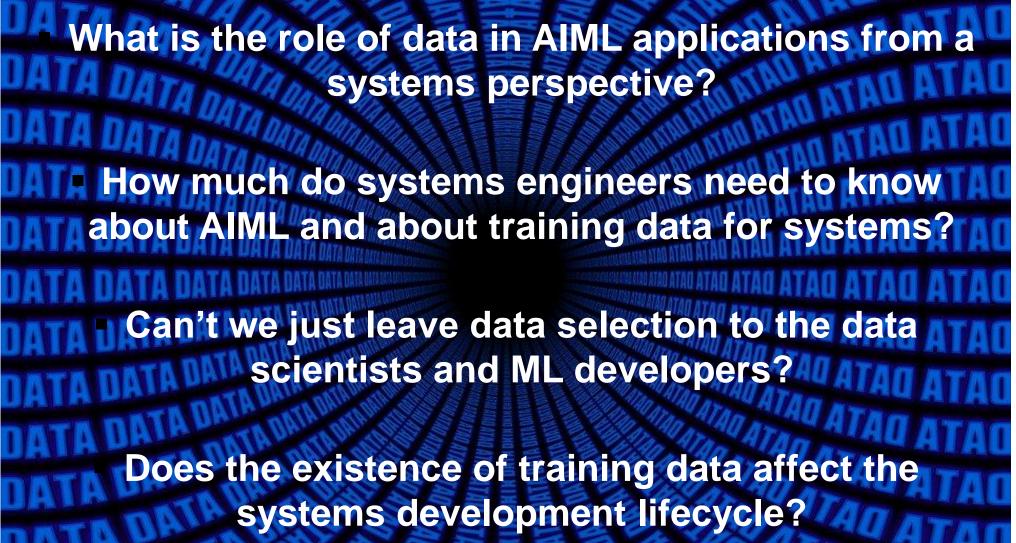
- Ramakrishnan (Ramki) Raman is currently Principal Systems Engineer at Honeywell. He is a certified Six Sigma Black Belt and is INCOSE Certified Expert Systems Engineering Professional – ESEP, and IEEE Systems Council Distinguished Lecturer
- Ramki's areas of interest includes complex systems and system-ofsystems, and artificial intelligence machine learning, and he has several publications in peer reviewed international journals & conferences on these areas



- Ramki is active in the professional societies, including INCOSE, IEEE, and SAE. He is currently serving as Assistant Director INCOSE Asia Oceania, and as Chair of IEEE Bangalore Section Systems Council Chapter. He is a recipient of INCOSE Outstanding Service Award in 2016. He has also been the Technical Program Chair for international conferences including 2016 & 2019 Asia Oceania Systems Engineering Conference, and 31st INCOSE International Symposium.
- Ramki actively interacts with various academic institutions, and is currently Guest Faculty at IIT Bombay, and Adjunct Faculty at Manipal Institute of Technology

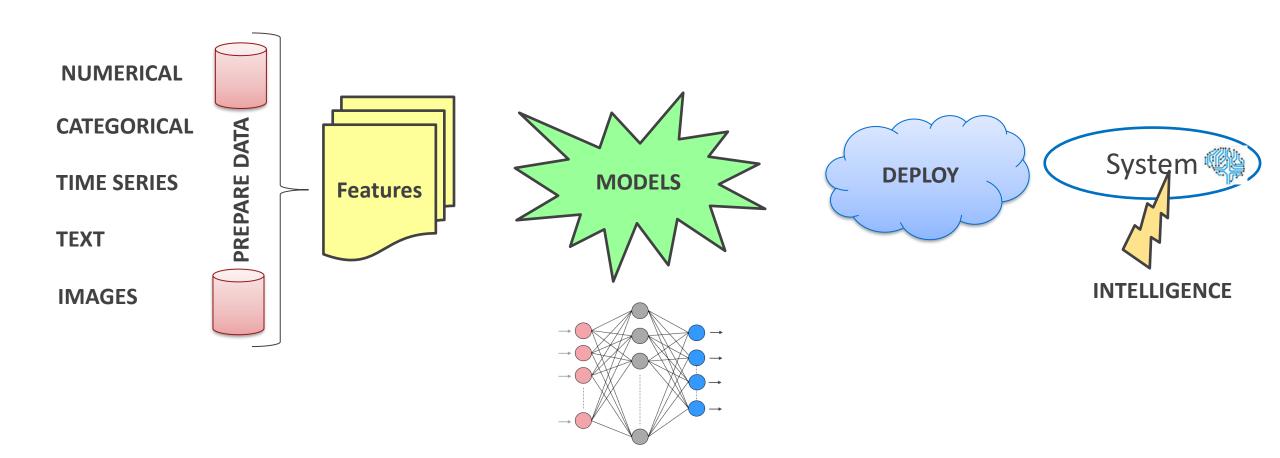
#### **Agenda in Questions**







## Context: Generic Workflow

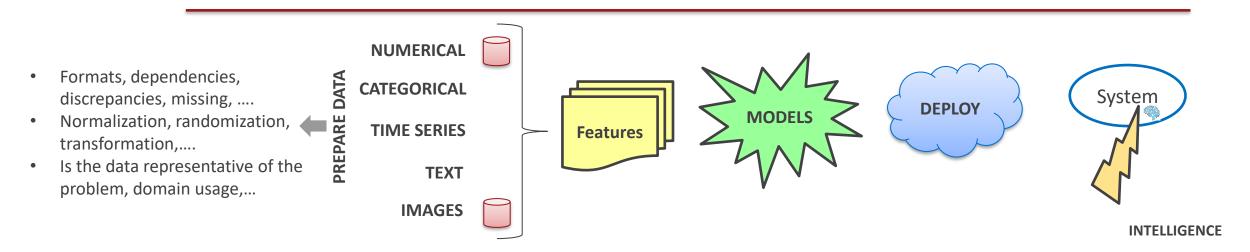




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# But it's more than what meets the eye...

- What is the intelligence that is required for the system? What are the desired behaviors? What are the desired performance levels? What are the acceptable tolerances for errors/ false-positives/ false negative etc.?
- What is the source data on which the intelligence can be built? What are the data types? What are the
  restrictions on usage of the data? What should be the training, validation & test data sets? What could be
  potential features?
- What are the potential approaches to build the intelligence model? Neural Networks, SVM, Decision tree ... etc.? What are the specific topologies/ parameters that need to be decided/ configured?



#### **Quick Quiz:**



## Training data in AIML applications is most similar to what in traditional software development:

- a. Test data
- b. Configuration settings
- c. Compiled object code
- d. Source code
- e. Database

SE Pathways to Al Now

# Als are dangerous because they get things wrong for unknown reasons



#### Data Requirements: The Green School Bus Problem

Al image recognition is taught to identify military vehicles and differentiate civilian





https://pixabay.com/photos/tank-panzer-

battle-tank-gun-2729903/, free

https://pixabay.com/photos/us-armyunited-states-army-oshkosh-2526749/, free



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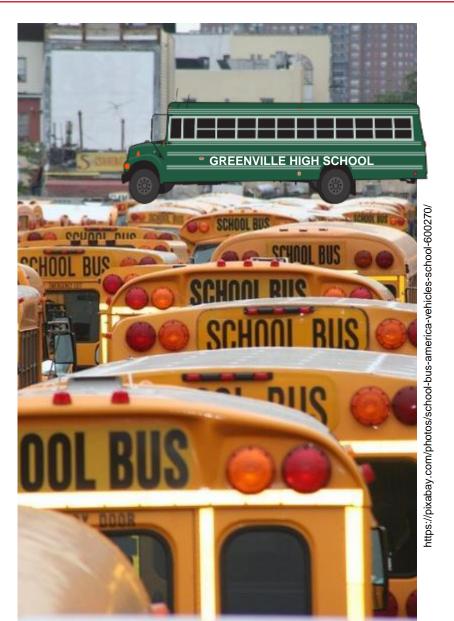
# Now, into the field of view wanders this:



#### How will the green school bus be identified?

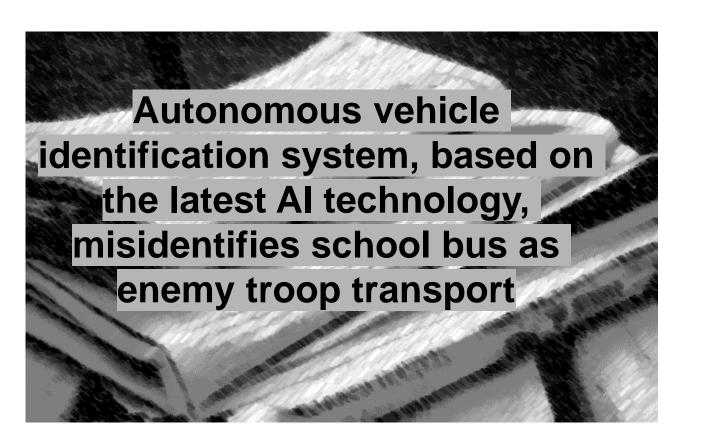


- a) School bus
- b) Tank
- c) Aston Martin DB9
- d) Military Truck
- e) Sort of like a school bus, but a color never seen before
- f) Image not recognized



#### **Imagining the Nightmare Headline**





#### Who is at fault?

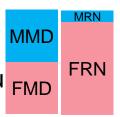
- a) Someone else (not me)
- b) Systems engineer
- c) Data scientist
- d) ML developer
- e) Tester
- Program manager

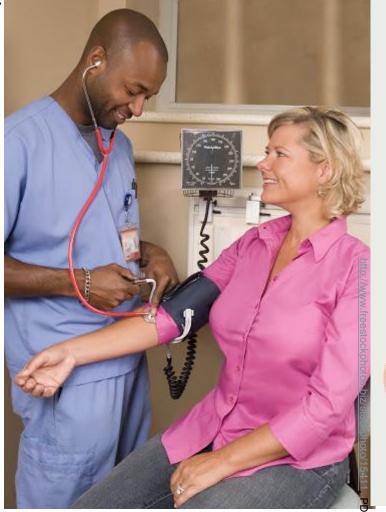
#### **Data and Bias**



Systems Thinking: use an unreal world to counter bias

- Bias in the world vs. bias in the data Application: identify male nurses and female nurses in photos
- In the world: 93% of nurses are female
- Should data consist of 93% female nurse photos?
- A "real world" dataset might do poorly on male nurses
- Expand application to all hospital personnel
  - Among MDs, 50% are female
  - In our real world set, most men are doctors and most women are
  - Likely misclassification of male nurses as doctors and female doctors as nurses!
- Better dataset would be 50/50 on both m/f doctors and nurses
- Can use conditional probability to reason about data, e.g. P(female | nu







### Toward a Data Requirements Approach



- New kind of requirements, similar to the "-ilities" (reliability, maintainability, dependability, safety, security)
- Must develop specific language to describe data requirements
  - Not "System shall use the right data…"
  - Just like not "System shall be easy to use"
  - Or, "System shall be explainable"

#### **Data Requirements**

Not your DADS requirements

- D Diversity
- A Augmentation
- D Distribution
- S Synthesis

### **D** – Diversity of Data



- Al does not generalize as we do
  - Counter-intuitive from human perspective; child can generalize with VERY few examples
- Need images of every size, type and color
- Must understand what is expected in the intended environment
- Systems Engineers must specify the data and its diversity

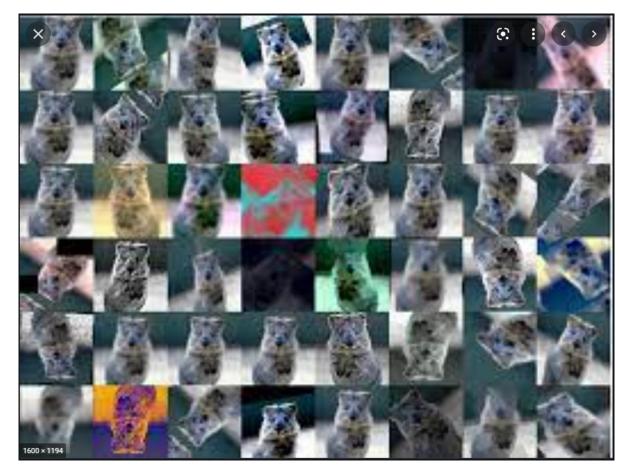


SE Pathways to Al Now

#### A – Augmentation of Data

INCOSE

- Software-generated variations of training data
- Ideally, include every variation that Almight see in deployed application
  - Colors, lighting, angles, backgrounds
  - Angle can change apparent shape of object
  - Not all angles are likely
- Vary the images to "teach" the AI that the category variations are still the same category
- Systems engineers must specify what variations should be included
- Data scientists can suggest others to improve model accuracy
  - What augmentation might be **required** for this application?



#### D – Distribution of Data



- Must have enough images of each required category to train system well
- Must not introduce bias due to insufficient training data
- Evaluate by measuring accuracy on various classes
- Systems engineers must be aware of "non-essential" distribution in the world, e.g. m/f nurses vs. "essential" features like tanks have tracks



SE Pathways to Al Now

#### S – Synthesis of New of Data



- New training data generated by computer
- Synthesized data can result in effective training
- Example: horses and humans dataset, CGI Photoreal generation (Laurence Moroney)
- Rules, scenarios and other methods can generate example data for training, then allow the AI to learn from it





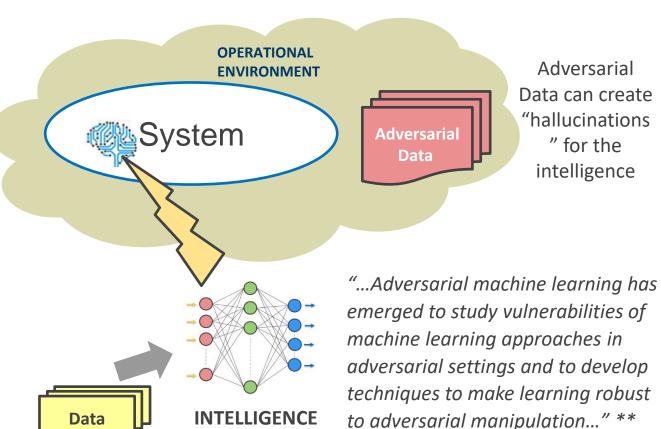
# Intelligence Implications of Data

Intelligence is as good as the data used to develop the intelligence....

- Is the operational environment benign?
- Is the "Data" used for developing the intelligence representative of the operational environment?



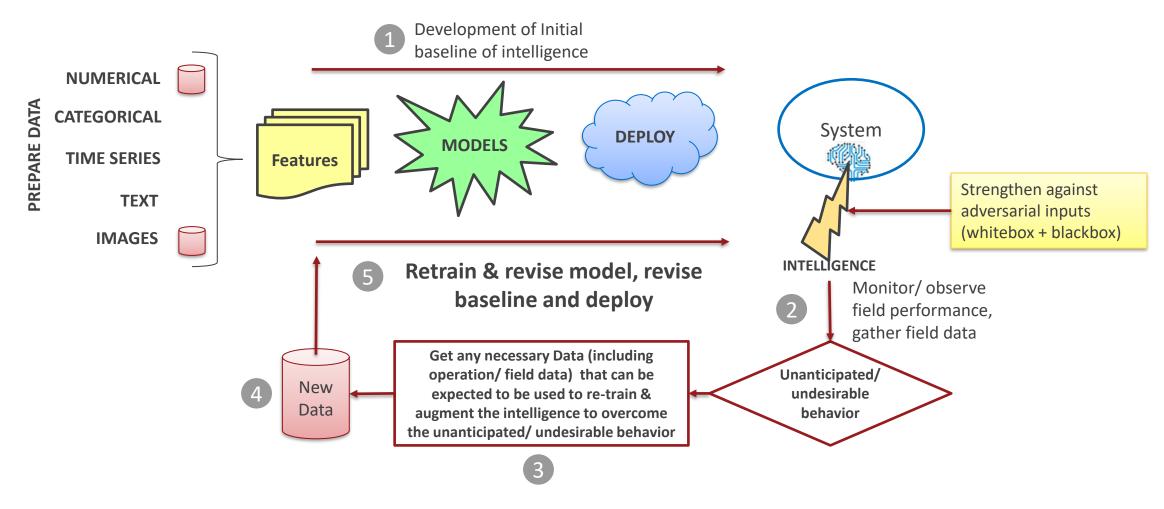
https://www.wired.com/story/researcher-fooled-a-google-ai-into-thinking-a-rifle-was-a-helicopter/



<sup>\*\*</sup> Vorobeychik, Y. and Kantarcioglu, M., 2018. Adversarial machine learning. Synthesis Lectures on Artificial Intelligence and Machine Learning, 12(3)



# Intelligence – Baselines & Updates



### Wrapping Up



#### Key take-aways

- Systems engineers must be aware of the role of training data
- Systems engineers must specify data based on the application and environment, with collaboration from data scientists
- Key areas of data requirements (DADS)
  - Diversity
  - Augmentation
  - Distribution
  - Synthesis
- Data has its own lifecycle that must be managed within the larger system development lifecycle

