PROCEEDINGS OF SPIE

Signal Processing, Sensor/Information Fusion, and Target Recognition XXXI

Ivan Kadar
Erik P. Blasch
Lynne L. Grewe
Editors

3–7 April 2022
Orlando, Florida, United States

6–12 June 2022
ONLINE

Sponsored and Published by
SPIE

Volume 12122

Proceedings of SPIE 0277-786X, V. 12122

SPIE is an international society advancing an interdisciplinary approach to the science and application of light.

Signal Processing, Sensor/Information Fusion, and Target Recognition XXXI, edited by
Ivan Kadar, Erik P. Blasch, Lynne L. Grewe, Proc. of SPIE Vol. 12122,
1212201 · © 2022 SPIE · 0277-786X · doi: 10.1117/12.2644472

The papers in this volume were part of the technical conference cited on the cover and title page. Papers were selected and subject to review by the editors and conference program committee. Some conference presentations may not be available for publication. Additional papers and presentation recordings may be available online in the SPIE Digital Library at SPIEDigitalLibrary.org.

The papers reflect the work and thoughts of the authors and are published herein as submitted. The publisher is not responsible for the validity of the information or for any outcomes resulting from reliance thereon.

Please use the following format to cite material from these proceedings:
Author(s), "Title of Paper," in *Signal Processing, Sensor/Information Fusion, and Target Recognition XXXI*, edited by Ivan Kadar, Erik P. Blasch, Lynne L. Grewe, Proc. of SPIE 12122, Seven-digit Article CID Number (DD/MM/YYYY); (DOI URL).

ISSN: 0277-786X
ISSN: 1996-756X (electronic)

ISBN: 9781510651203
ISBN: 9781510651210 (electronic)

Published by
SPIE
P.O. Box 10, Bellingham, Washington 98227-0010 USA
Telephone +1 360 676 3290 (Pacific Time)
SPIE.org

Printed in the United States of America by Curran Associates, Inc., under license from SPIE.

Publication of record for individual papers is online in the SPIE Digital Library.

SPIE. DIGITAL LIBRARY

SPIEDigitalLibrary.org

Paper Numbering: A unique citation identifier (CID) number is assigned to each article in the Proceedings of SPIE at the time of publication. Utilization of CIDs allows articles to be fully citable as soon as they are published online, and connects the same identifier to all online and print versions of the publication. SPIE uses a seven-digit CID article numbering system structured as follows:

- The first five digits correspond to the SPIE volume number.
- The last two digits indicate publication order within the volume using a Base 36 numbering system employing both numerals and letters. These two-number sets start with 00, 01, 02, 03, 04, 05, 06, 07, 08, 09, 0A, 0B … 0Z, followed by 10-1Z, 20-2Z, etc. The CID Number appears on each page of the manuscript.

Contents

SESSION 8 SIGNAL AND IMAGE PROCESSING, AND INFORMATION FUSION APPLICATIONS II

SESSION 9 SIGNAL AND IMAGE PROCESSING, AND INFORMATION FUSION APPLICATIONS III

SESSION 10 SIGNAL AND IMAGE PROCESSING, AND INFORMATION FUSION APPLICATIONS IV

POSTER SESSION

Conference Committee

Symposium Chairs

Augustus W. Fountain III, University of South Carolina (United States)
Teresa L. Pace, L3Harris Technologies, Inc. (United States)

Conference Chairs

Ivan Kadar, Interlink Systems Sciences, Inc. (United States)
Erik P. Blasch, Air Force Research Laboratory (United States)
Lynne L. Grewe, California State Univ., East Bay (United States)

Conference CoChairs

Bhashyam Balaji, Defence Research and Development Canada (Canada)
Thia Kirubarajan, McMaster University (Canada)

Conference Program Committee

William D. Blair, Georgia Tech Research Institute (United States)
Mark J. Carlotto, General Dynamics Advanced Information Systems (United States)
Alex L. Chan, U.S. Army Research Laboratory (United States)
Kuo-Chu Chang, George Mason University (United States)
Chee-Yee Chong, Independent Consultant (United States)
Frederick E. Daum, Raytheon Company (United States)
Jean Dezert, The French Aerospace Laboratory (France)
Laurie H. Fenstermacher, Air Force Research Laboratory (United States)
Jon S. Jones, Independent Consultant (United States)
Georgiy M. Levchuk, Aptima, Inc. (United States)
Martin E. Liggins II, Independant Consultant (United States)
James Llinas, University at Buffalo (United States)
Uttam Majumder, Air Force Research Laboratory (United States)
Raj P. Malhotra, Air Force Research Laboratory (United States)
Alastair D. McAulay, Lehigh University (United States)
Raman K. Mehra, Scientific Systems Co., Inc. (United States)
Harley R. Myler, Lamar University (United States)
John J. Salerno Jr., Harris Corporation (United States)

Robert W. Schutz, Consultant (United States)
Andrew G. Tescher, AGT Associates (United States)
Stelios C. A. Thomopoulos, National Center for Scientific Research Demokritos (Greece)
Shanchieh Jay Yang, Rochester Institute of Technology (United States)

Data Fusion Learning Enhanced Xabilities Analysis

(Panel: SPIE Defense & Commercial Sensing)

30 years

4 April 2022 • 1:20 PM – 4:00 PM PDT

SPIE Panel

Panel Organizers: Erik P. Blasch, MOVEJ Analytics / Air Force Research Lab.
Ivan Kadar, Interlink Systems Sciences, Inc., USA;

Panel Moderators: Lynne Grewe, California State Univ., USA
Chee-Yee Chong, Independent Consultant

Panelists: Genshe Chen - Intelligent Fusion Technology, Inc.
Yu Chen – Binghamton University
Andreas Savakis – Rochester Institute of Technology
Yufeng Zheng - University of Mississippi Medical Center

Conference: Signal Processing, Sensor/Information Fusion, and Target Recognition

Panel Members

- **Panel Organizers**: Erik P. Blasch, MOVEJ Analytics / Air Force Research Lab.
  Ivan Kadar, Interlink Systems Sciences, Inc., USA;
- **Panel Moderators**: Lynne Grewe, California State Univ., USA
  Chee-Yee Chong, Independent Consultant

- **Panelists (Alphabetical):**
- Erik P. Blasch, MOVEJ Analytics
- Genshe Chen - Intelligent Fusion Technology, Inc.
- Yu Chen – Binghamton University
- Lynne Grewe, California State Univ., USA
- Andreas Savakis – Rochester Institute of Technology
- Yufeng Zheng - University of Mississippi Medical Center

SPIE Panel: Joint Data Learning (1)

- **ABSTRACT:** The panel brings together experts to focus on the Xabilities analysis over multi-source data, modeling, and tasks in domains of static (off-line), dynamic (on-line), and usable (in-line) learning methods.
- All of these requirements motivate the need for addressing data curation, metrics development, relevance assessment, human involvement, and system coordination. Looking holistically, these Xabilities motivate pragmatic thought and analysis for SDF design of concepts and outputs.
- (1) **design** (explainability, interpretability),
- (2) **evaluation** (verifiability, robustness),
- (3) **test** (validity, certifiability) and
- (4) **deployment** (reliability, accountability, sustainability).
- There are a variety of questions to be discussed, explored, and analyzed for fusion-based AI tool.

Conference: Signal Processing, Sensor/Information Fusion, and Target Recognition

Joint Data Learning (2)

- **Questions**
- 1. Name your **top 5 abilities** you think are important (e.g., explainability)?
- 2. Is there an **overlap on the metrics** and current data fusion research?
- 2. Every year for data fusion, metrics are discussed as needing **standardization**, hence, is there progress?
- 4. Which "ability" is nice, but **not needed** (e.g., ethic-ability)
- 5. Which "ability" would **see progress** in the next 5 years of importance for fusionists?

x

Prior Panels

- E. Blasch, Andreas Savakis, Yufeng Zhen, Genshe Chen, Ivan Kadar, Uttam Majumder, Ali K Raz, "Joint Data Learning Panel Summary," *Proc. SPIE 12122*, 2022.
- E. Blasch, L. L. Grewe, E. L. Waltz, P. Bendich, V. Pavlovic, I. Kadar, C-Y. Chong, "Machine learning in/with information fusion for infrastructure understanding, panel summary," *Proc SPIE 11423*, 2020.
- E. Blasch, I. Kadar, L. L. Grewe, G. Stevenson, U. K. Majumder, C.-Y. Chong, "Deep learning in AI and information fusion panel discussion," *Proc. SPIE, 11018*, 2019.
- E. Blasch, I. Kadar, L. L. Grewe, R. Brooks, W. Yu, A. Kwasinski, S. Thomopoulos, J. Salerno, H. Qi, "Panel Summary of Cyber-Physical Systems (CPS) and Internet of Things (IoT) Opportunities with Information Fusion," *Proc. SPIE*, Vol. 10200, 2017.
- E. Blasch, I. Kadar, C-Y. Chong, A. Steinberg, R. P. S. Mahler, S. J. Yang, L. H. Fenstermacher, A. L. Chan, P. Tandy, "Issues and Challenges of Applications of Context to Enhance Information Fusion, Panel Summery," *Proc. SPIE*, Vol. 9842, 2016.
- E. Blasch, I. Kadar, C-Y. Chong, E. K. Jones, J. E. Terno, L. Fenstermacher, J. D. Gorman, G. Levchuk, "Issues and Challenges of Information Fusion in Contested Environments: Panel Results," *Proc. SPIE*, Vol. 9474, 2015.C-Y. Chong, E. Blasch, I. Kadar, J. D. Gorman, J. E. Tierno, E. K. Jones, G. Levchuk, L. Fenstermacher, "Invited Panel Discussion: Issues and Challenges of Information Fusion in Contested Environments," *Proc. SPIE*, Vol. 9091, 2014.
- E. Blasch, J. J. Salerno, I. Kadar, S. J. Yang, L. H. Fenstermacher, M. Endsley, L. L. Grewe, "Summary of Human, Social, Cultural, Behavioral (HSCB) modeling for Information Fusion panel discussion," *Proc. SPIE*, Vol. 8745, 2013.

Panel

SPIE. DEFENSE+ COMMERCIAL SENSING


Ivan Kadar


Erik P. Blasch

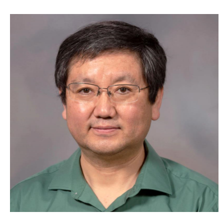

Lynne Grewe


Chee-Yee Chong


Genshe Chen


Yu Chen


Andreas Savakis

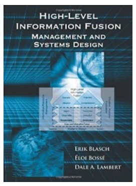

Yufeng Zheng

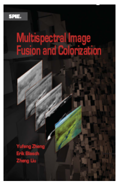
Data Fusion Learning X-Abilities

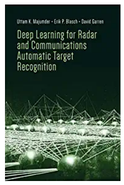
(Panel: SPIE Defense & Commercial Sensing)

4 April 2022 • 1:20 PM - 4:20 PM

SPIE Panel







Erik Blasch

MOVEJ Analytics

Conference: Signal Processing, Sensor/Information Fusion, and Target Recognition

Sensor Data Fusion

Physics-based /Human-derived Information Fusion (PHIF)

Invited Panel: Data Fusion Leaning xAbilities

- Panel: Heterogeneous Data Fusion Learning for Enhanced Xabiilties Analysis

Current efforts in sensor data fusion (SDF) and artificial intelligence/machine learning (AI/ML) include analysis over:

design (explainability, interpretability),
evaluation (verifiability, robustness),
test (validity, certifiability) and
deployment (reliability, accountability, sustainability).

All of these requirements motivate the need for addressing data curation, metrics development, relevance assessment, human involvement, and system coordination. Looking holistically, these Xabilities motivate pragmatic thought and analysis for SDF design of concepts and outputs. For example, the SDF systems analysis includes the perceptual reasoning machine (PRM), data fusion information group (DFIG) process model, and an uncertainty fusion ontology (UFO) for data reduction, information gain, and knowledge enhancement. The panel brings together experts to focus on the Xabilities analysis over multi-source data, modeling, and tasks in domains of static (off-line), dynamic (on-line), and usable (in-line) learning methods.

Invited Panel: Data Fusion Leaning xAbilities

- Panel: Heterogeneous Data Fusion Learning for Enhanced Xabiilties Analysis

Chairs:

- **Erik Blasch**, Air Force Research Lab. (USA);
- **Lynne L. Grewe**, California State Univ., East Bay (USA);
- **Ivan Kadar**, Interlink Systems Sciences, Inc. (USA);
- **Chee-Yee Chong**, Consultant (USA)

Panelists

- **Genshe Chen** - Intelligent Fusion Technology, Inc.
- **Yu Chen** – Binghamton University (SUNY)
- **Andreas Savakis** – Rochester Institute of Technology
- **Yufeng Zheng** - University of Mississippi Medical Center

Metrics of analysis of AI (Deep Learning and Machine Learning)

Invited Panel: Data Fusion Leaning xAbilities

- **Panel: Heterogeneous Data Fusion Learning for Enhanced Xabiilties Analysis**

Questions

- **1. Name your top 5 abilities you think are important (e.g., explainability)?**
- **2. Is there an overlap on the metrics and current data fusion research?**
- **3. Every year for data fusion, metrics are discussed as needing standardization, hence, is there progress?**
- **4. Which "ability" is nice, but not needed (e.g., ethic-ability)**
- **5. Which "ability" would see progress in the next 5 years of importance for fusionists?**

DOD Principles of Artificial Intelligence

Principles of AI
- Responsible
- Equitable
- Traceable
- Reliable
- Governable

Principles of Data
- Visible
- Available
- Understandable
- Linked
- Trusted

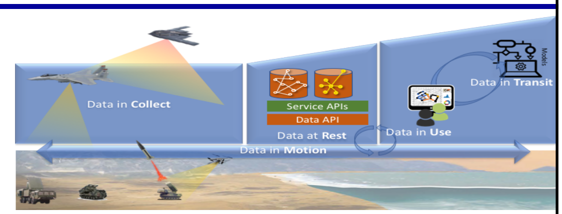
https://www.defense.gov/Explore/News/Article/Article/2094085/dod-adopts-5-principles-of-artificial-intelligence-ethics/

Dynamic Data Systems Workshop

- **People**: Government, Academia, Industry
- **Topics**: Multi-Domain Command and Control (MDC2), ISR, Predictive Maintenance (PM) and Clouds (IoT)
- **Recommendations:**

R1: Support enterprise-level federated **service-based architecture**;
R2: Extend the Multi-Domain MDM (Master Data Management) to **include real-time multidimensional and dynamic data**, and data from models;
R3: Provide data for performance analysis and benchmarking;
R4: Adjudicate proactive **sharing of data based on need to know with intelligent granularity**; and
R5: Incorporate models interacting with data in a **feed-back control loop.**

- **Visible**
- **Accessible**
- **Understandable**
- **Linked**
- **Trusted**



Data at Rest: Develop a *Data as a service (DaaS)* architecture that incorporates contextual information, metadata, and registration;
Data in Collect: Provide *structure (e.g., translations)* between data for integration, analysis, and storage;
Data in Transit: Leverage the *power of modeling* from which data is analyzed for information and delivered as knowledge;
Data in Use: Afford data-based *needs collections* (recommendations) based on dynamic mission priorities, and balanced between need to know and need to share; and
Data in Motion: Utilize *feedback control loops* to dynamically adapt to changing priorities, timescales, and mission collects.

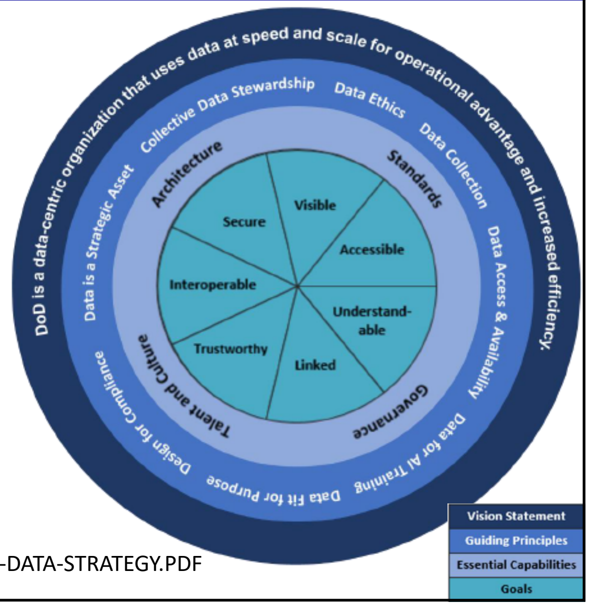
F. Darema, E. Blasch, et al., "*Air Force Chief Data Officer Workshop Report on Dynamic Data Systems,*" AF Chief Data Office, Dec. 2018. (88ABW-2019-408)

DoD Data Strategy

- Sept 2020 – VAULTIS – **make data**

1.) ***Visible –*** Consumers can locate the needed data.
2.) ***Accessible –*** Consumers can retrieve the data.
3.) ***Understandable –*** Consumers can recognize the content, context, and applicability.
4.) ***Linked –*** Consumers can exploit data elements through innate relationships.
5.) ***Trustworthy –*** Consumers can be confident in all aspects of data for decision-making.

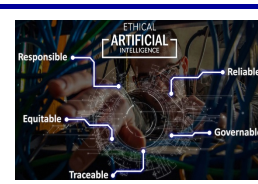
6.) ***Interoperable –*** Consumers have a common representation/comprehension of data.
7.) ***Secure –*** Consumers know that data is protected from unauthorized use/manipulation.



https://media.defense.gov/2020/Oct/08/2002514180/-1/-1/0/DOD-DATA-STRATEGY.PDF

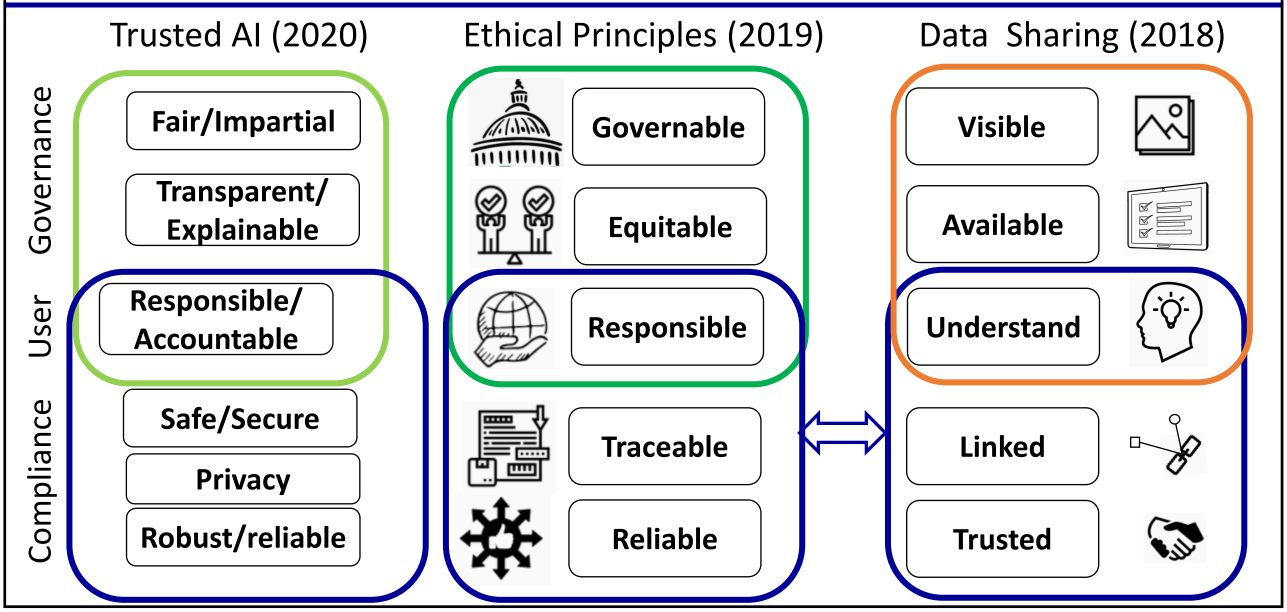
DOD Principles of Artificial Intelligence

- **Responsible**: DOD personnel will exercise **appropriate levels of judgment** and care while remaining responsible for the development, deployment and use of AI capabilities.
- **Equitable** : The department will take deliberate steps to **minimize unintended bias** in AI capabilities.
- **Traceable**: The department's AI capabilities will be developed and deployed such that relevant personnel possess an appropriate understanding of the technology, development processes and operational methods applicable to AI capabilities, including with **transparent and auditable methodologies, data sources and design procedures and documentation**.
- **Reliable**: The department's AI capabilities will have explicit, **well-defined uses**, and the **safety, security and effectiveness** of such capabilities will be subject to testing and assurance within those defined uses across their entire life cycles.
- **Governable**: The department will design and engineer AI capabilities to fulfill their **intended functions** while possessing the ability to detect and avoid unintended consequences, and the ability to disengage or deactivate deployed systems that demonstrate unintended behavior



https://www.defense.gov/Explore/News/Article/Article/2094085/dod-adopts-5-principles-of-artificial-intelligence-ethics/

AI Policies



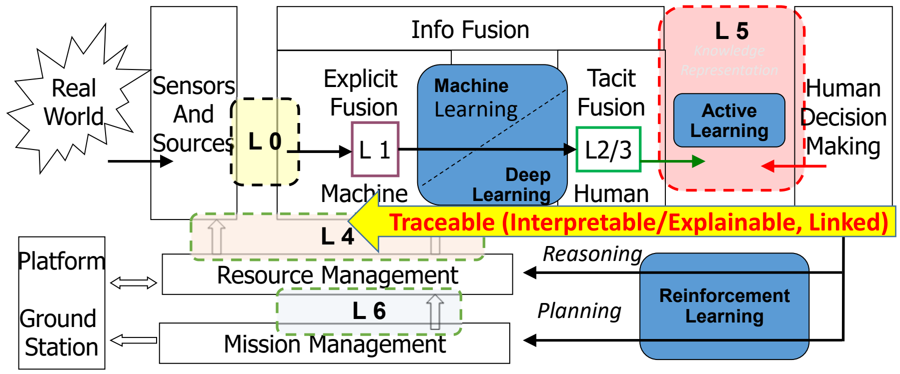
Q1: Panel: Data Fusion Leaning xAbilities

- **Q1: Name your top 5 abilities you think are important (e.g., explainability)?**

- **Responsible**: DOD personnel will exercise **appropriate levels of judgment** and care while remaining responsible for the **development, deployment and use** of AI capabilities.
- **Traceable (Interpretable/Explainable, Linked)**: The department's AI capabilities will be developed and deployed such that relevant personnel possess an appropriate understanding of the technology, development processes and operational methods applicable to AI capabilities, including with **transparent and auditable methodologies, data sources and design procedures and documentation**.
- **Reliable (Robust/Trusted)** : The department's AI capabilities will have explicit, **well-defined uses**, and the **safety, security and effectiveness** of such capabilities will be subject to testing and assurance within those defined uses across their entire life cycles.
- **Governable**: The department will design and engineer AI capabilities to fulfill their **intended functions** while possessing the ability to detect and avoid unintended consequences, and the ability to disengage or deactivate deployed systems that demonstrate unintended behavior

Q2: Panel: Data Fusion Leaning xAbilities

- **Q2: Is there an overlap on the metrics and current data fusion research?**

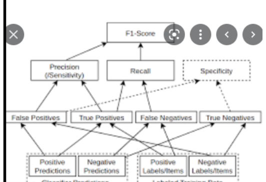


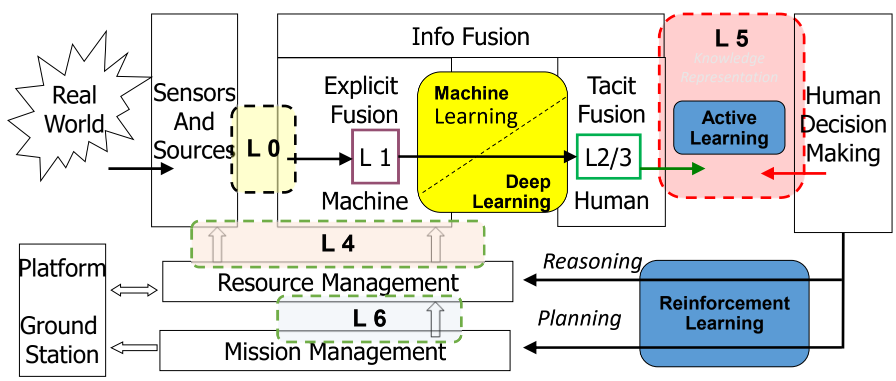
- **Traceable (Interpretable/Explainable, Linked):** AI deployed such that relevant personnel possess an appropriate understanding of the technology, development processes and operational methods applicable to AI capabilities, including with **transparent and auditable methodologies, data sources and design procedures and documentation**.

Q3: Panel: Data Fusion Leaning xAbilities

- **Q3: Every year for data fusion, metrics are discussed as needing standardization, hence, is there progress?**

- **AI : Metrics**
- **F1**
- **Mean Average Precision**
- **Accuracy**
- **Confusion Matrix**





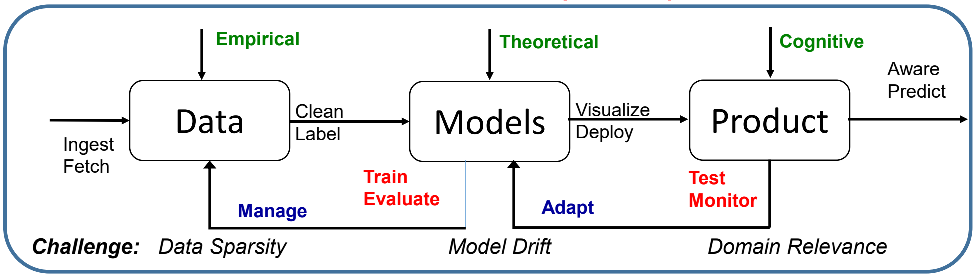
Joint Data Learning :Q5: Standards

- 5) what is the future - such as a standard or evaluation method

Evaluation (e.g., STANAG 2511, 4162)

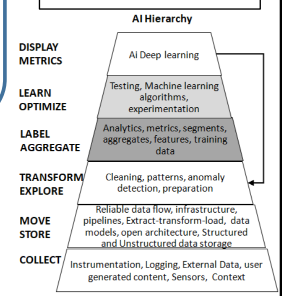
Multisource AI Scorecard Table (MAST)

2019 PUBLIC-PRIVATE ANALYTIC EXCHANGE PROGRAM



ICD203 Standards

1. Sourcing
2. Uncertainty
3. Distinguishing
4. Analysis of Alternatives
5. Customer Relevance
6. Logical Argumentation
7. Consistency
8. Accuracy
9. Visualization

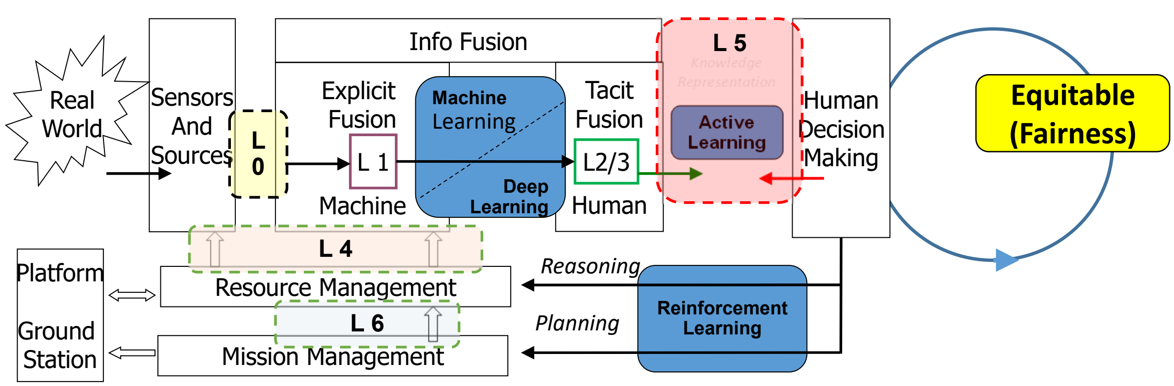


- **Intelligence Community Directive 203 – Analytic Standards**
  - Test and Evaluation of AI/ML systems

E. Blasch, J. Sung, T. Nguyen, "Multisource AI Scorecard Table for System Evaluation," *AAAI FSS-20: Artificial Intelligence in Government and Public Sector*, 2020. arXiv:2102.03985

Q4: Panel: Data Fusion Leaning xAbilities

- **Q4: Which "ability" is nice, but not needed (e.g., ethic-ability)**

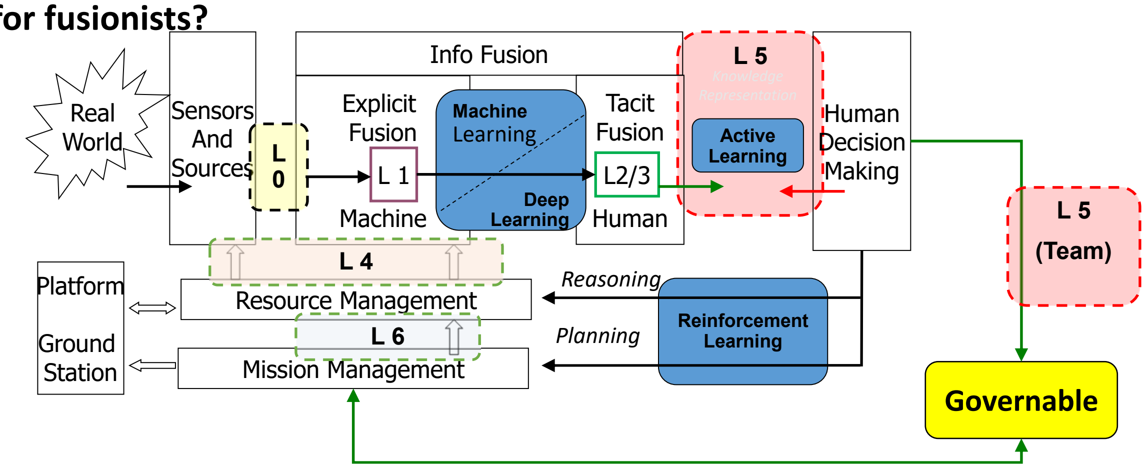


- **Equitable** : The department will take deliberate steps to **minimize unintended bias** in AI capabilities.
- **Data** : It is the data from which inequitable results may be important, needed. Thus hard to disambiguate.

xix

Q5: Panel: Data Fusion Leaning xAbilities

- **Q5: Which "ability" would see progress in the next 5 years of importance for fusionists?**



- **Governable**: design and engineer AI capabilities to fulfill their **intended functions**

Invited Panel: Data Fusion Leaning xAbilities

- **Panel: Heterogeneous Data Fusion Learning for Enhanced Xabiilties Analysis**

Questions

- **1. Name your top 5 abilities you think are important: traceability**
  Traceability – Trusted, Explainable, Interpretable, Linked
- **2. Is there an overlap on the metrics and current data fusion research?**
  Credibility – F1 (Precision/Recall) , Confusion Matrix (Accuracy), ROC
- **3. Every year for data fusion, metrics are discussed as needing standardization, hence, is there progress? (Not Yet)**
- **4. Which "ability" is nice, but not needed : ethical, *fairness***
- **5. Which "ability" would see progress in the next 5 years of importance for fusionists: governable**

xx

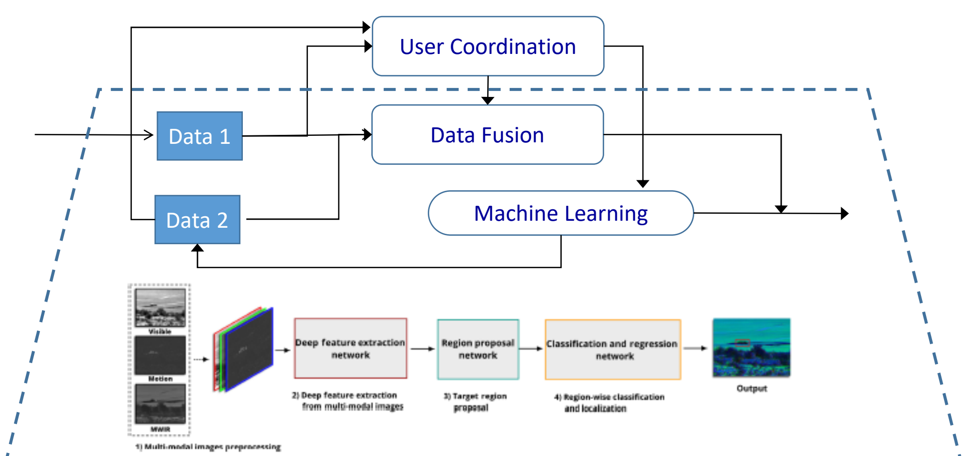
Joint Data Learning – Summary (2021)

- **Questions**
- 1) **Data fusion success** – AI/ML Active Learning
- 2) **Emerging applications** – Real-time Inspection
- 3) **Train a joint classifier** – Data Alignment
- 4) **Users** – Operators, but need to test AI/ML in the work domain
- 5) **Future** – AI/ML Data Fusion standards

Erik Blasch
MOVEJ Analytics

Joint Data Learning :Q1 – Data Fusion

- 1) Summarize a recent unique data fusion success stor



Shuo Liu, Huan Liu, Vijay John, Zheng Liu, Ying Huang, E. Blasch, "Enhanced Situation Awareness through CNN-based Deep MultiModal Image Fusion," *Optical Engineering*, 59(5): 053103, April 2020.

Joint Data Learning Q2: Emerging

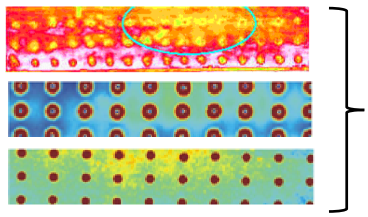
- 2) For joint data fusion (beyond multimedia and medicine) what are the next emerging applications? **Inspection, Targeting**

Y. Zheng. E. Blasch, Z. Liu, *Multispectral Image Fusion and Colorization*, SPIE Press, 2018.

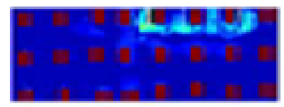
Ultrasonic

Eddy Current

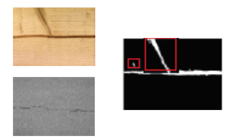
X-Ray



Fusion



- **Evidential Neural Networks (ENN)**
- **WGGAN – Wavelet Guided Generative Adversarial Network**
- Domain Adaptation/Transfer Learning

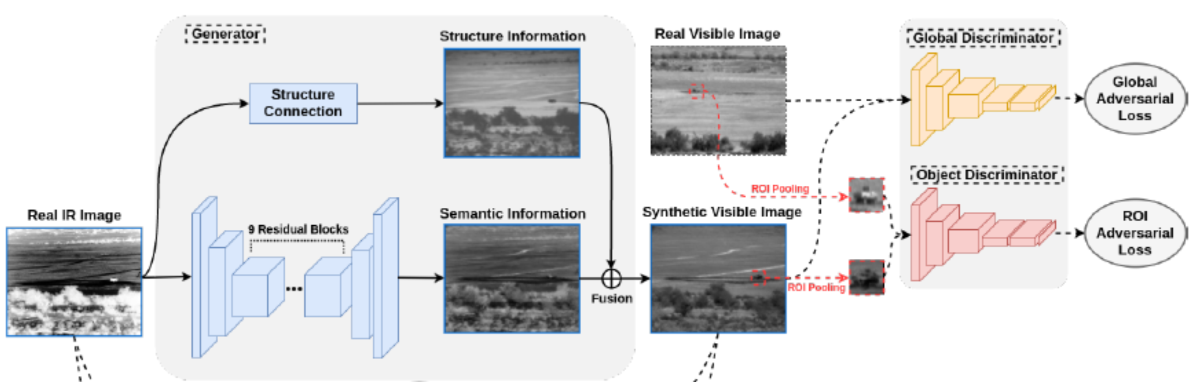


W. Zhai, J. Zhu, Y. Cao and Z. Wang, "A Generative Adversarial Network Based Framework for Unsupervised Visual Surface Inspection," *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2018.

R. Zhang, J. Bin, Z. Liu, E. Blasch, "WGGAN: A **Wavelet-Guided Generative Adversarial Network** for Thermal Image Translation," *Generative Adversarial Networks for Image-to-Image Translation* , Elsevier, edited by M Naved, 2021

Joint Data Learning :Q3: Preparation

- 3) How to train a joint classifier - issues and preparations
- **Data Alignment**



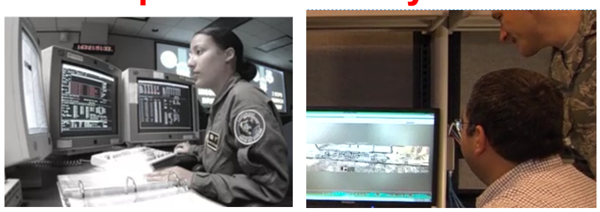
S. Liu, M. Gao, V. John. Z. Liu, E. Blasch, "Deep Learning Thermal Image Translation for Night Vision Perception," ACM *Transactions on Intelligent Systems and Technology*, 12(1):1-18, Dec. 2020.

xxii

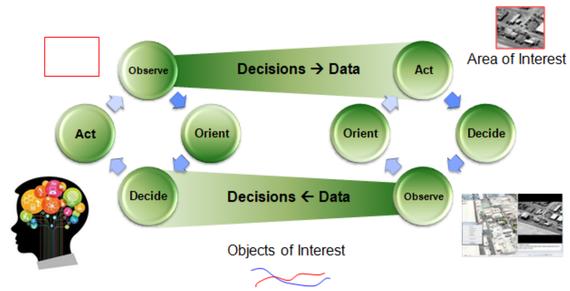
Joint Data Learning :Q4: Users

- 4) Who are the users that the DF/SF can support and subsequently the metrics of interest?

User/Operational Analyst



[Career as a USAF Space Systems Operator (thebalancecareers.com)]



Human-Machine Teaming - Observe-Orient-Decide-Act (OODA) loops
Metrics – Trust, Explainability, Interpretability, Usability, Understandability,

E. Blasch, A. Steinberg, S. Das, J. Llinas, C.-Y. Chong, O. Kessler, E. Waltz, and F. White, "Revisiting the JDL model for information Exploitation," *Int'l Conf. on Info Fusion*, 2013.

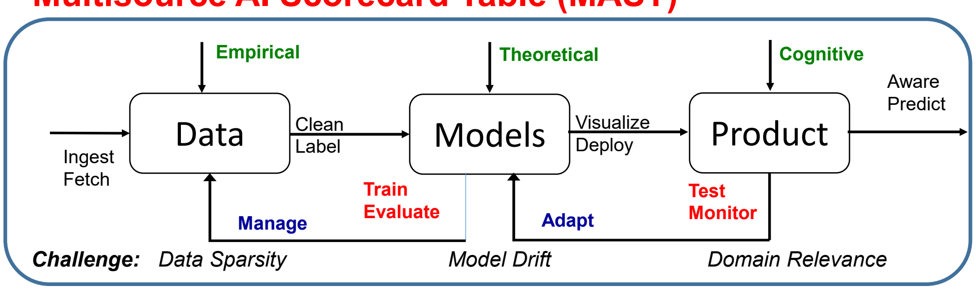
Joint Data Learning :Q5: Standards

- 5) what is the future - such as a standard or evaluation method

Evaluation (e.g., STANAG 2511, 4162)

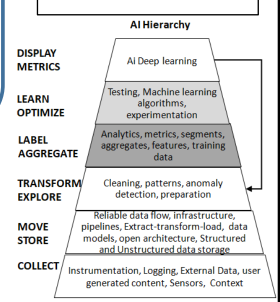
Multisource AI Scorecard Table (MAST)

2019 PUBLIC-PRIVATE ANALYTIC EXCHANGE PROGRAM



ICD203 Standards

1. Sourcing
2. Uncertainty
3. Distinguishing
4. Analysis of Alternatives
5. Customer Relevance
6. Logical Argumentation
7. Consistency
8. Accuracy
9. Visualization



- **Intelligence Community Directive 203 – Analytic Standards**
  - Test and Evaluation of AI/ML systems

E. Blasch, J. Sung, T. Nguyen, "Multisource AI Scorecard Table for System Evaluation," *AAAI FSS-20: Artificial Intelligence in Government and Public Sector*, 2020. arXiv:2102.03985

Joint Data Learning - Summary

- **Questions**
- 1) **Data fusion success** – AI/ML Active Learning
- 2) **Emerging applications** – Real-time Inspection
- 3) **Train a joint classifier** – Data Alignment
- 4) **Users** – Operators, but need to test AI/ML in the work domain
- 5) **Future** – AI/ML Data Fusion standards

Erik Blasch
MOVEJ Analytics

EXTRA: Explainable and Transparent Machine Learning for Autonomous Decision-Making

April 4, 2022

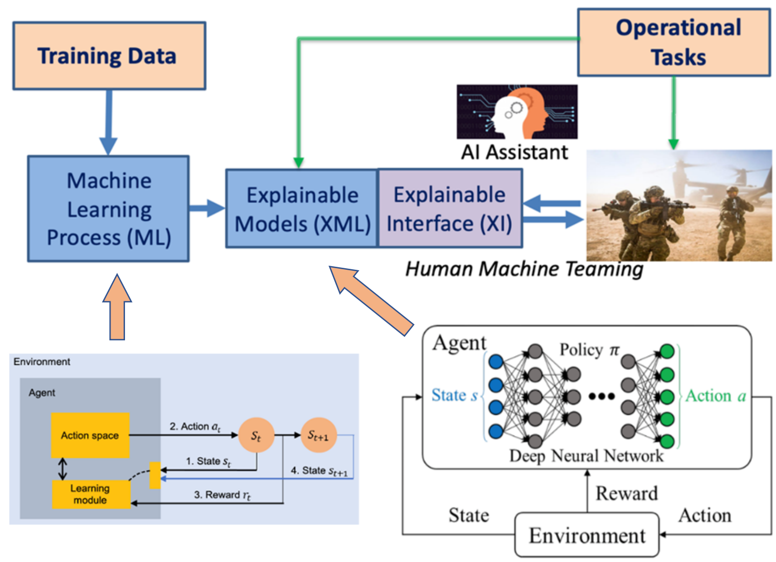
Intelligent Fusion Technology
Genshe Chen

Outline

- **EXTRA Framework and Technical Approaches**
- **Feasibility Test Use Cases**
- **Future work and Discussion**

EXTRA Framework – Explainable Deep Reinforcement Learning

- **POMDP Problem**
  - Current decision can affect future state and observations
  - Focus on long term objectives
- **Machine Learning**
  - Deep Reinforcement Learning (DRL) for complex sequential decision making
- **Explainable Models**
  - Explainable DRL (XDRL) ensures trusted autonomy
  - Enable human-machine teaming
- **Explainable Interface**
  - Intuitive explanations expressed with natural language derived from ontology-based domain knowledge graph



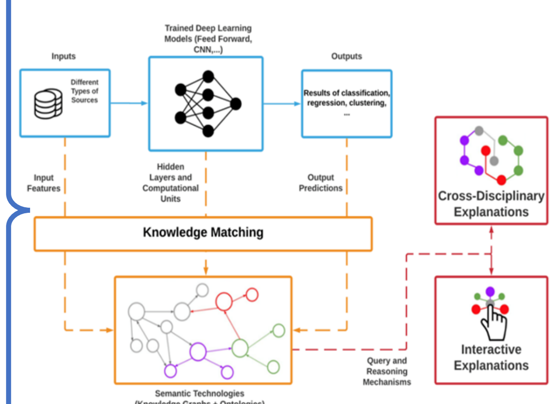
Technical Approaches

1. Reward Decomposition for Q-Learning in DRL
- Decompose reward function into meaningful type
- Compare action trade-offs among different types
- Learn the best policy while also learning the explanations

2. Bayesian Reinforcement Learning
- Provide a way to tackle the exploration-exploitation problem
- Provide a principled framework to represent uncertainty

3. Interpretable Deep Reinforcement Learning Algorithm
- Layer-wise reverse propagation to determine relevance features
- Bring explainability to highly complex deep neural networks

4. Explainable DRL with Ontologies and Knowledge Graph
- Encode entities and relations with semantic connections
- Present annotated interaction path for explicit explanation



* Giuseppe Futia and Antonio Vetrò, "On the Integration of Knowledge Graphs into Deep Learning Models for a More Comprehensible AI - Three Challenges for Future Research," *Information*, Feb., 2020.

Outline

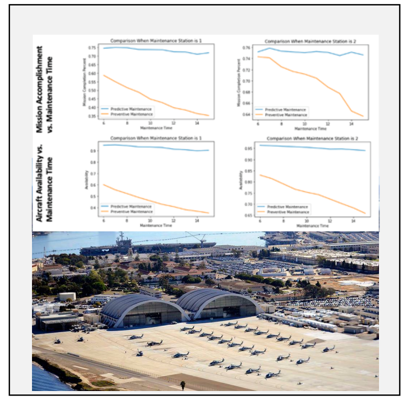
- EXTRA Framework and Technical Approaches
- Feasibility Test Use Cases
  - Aircraft Maintenance Scheduling
  - Space Situational Awareness
- Future Work and Discussion

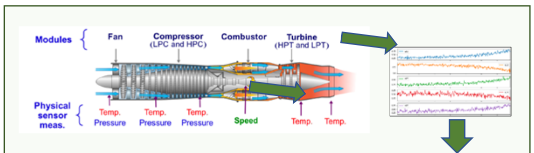
Maintenance and Mission Planning

- The aircraft fleet maintenance plays an important role to guarantee the safety and reliability of the fleet in commercial airlines and military air forces
  - The aircraft maintenance optimization is a multi-objective problem, which aims to maximize the operation revenue by maintaining high **mission readiness**, and at the same time to minimize the **maintenance cost.**
  - The aviation industry is highly regulated, meaning that aircraft must participate continuous inspection programs established by aviation authorities.
  - The fleet of aircraft has routine for detailed inspections or maintenance. Aircraft requires maintenance at various intervals, often known as flight line maintenance checks.
  - It is necessary to develop a maintenance strategy that is able to process the dynamic sequential maintenance scenario.
  - We propose to use **Reinforcement Learning** (**RL**) method as the optimization tool for aircraft maintenance decision making.

Aircraft Maintenance Scheduling – Objectives

- **Maximize the mission readiness**
  - Guarantee a sufficient number of available aircraft
  - Minimize aircraft fault in the mission
  - Reduce aircraft in the waiting list (queue) for maintenance
  - Optimize the usage of available maintenance resources
- **Minimize the maintenance cost**
  - Reduce the number of unnecessary maintenance

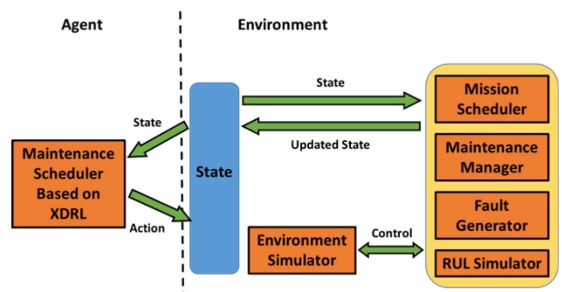




$$\max \frac{\left[\sum_{t=1}^{T}\sum_{k=1}^{K} M_t^k \cdot \left(\sum_{i=1}^{A_k}\left(1 - z_{it}^k\right)\right)\right]}{\left[\sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{i=1}^{A_k}\sum_{f=1}^{F} c_f^k x_{itf}^k\right]}$$

DRL Implementation Design

- **We decouple the environment into several modules**
  - Environment Simulator
    - Conduct the simulation according to the scenario description.
  - Mission Scheduler
    - Generate missions and requirements (β_t).
    - Assign missions to available aircrafts.
  - Maintenance Manager
    - Assign maintenance resources to aircrafts.
    - Determine available maintenance resources ($h_t \& n_t^k$).
  - Fault Generator
    - Generate accidental fault using certain stochastic models.
  - RUL (Remaining Useful Life) Simulator
    - Determine the RUL of each aircraft (D_i^k).
- **Potential Explainable approaches to be incorporated into the DRL solution**
  - Reward decomposition
  - Structure causal model

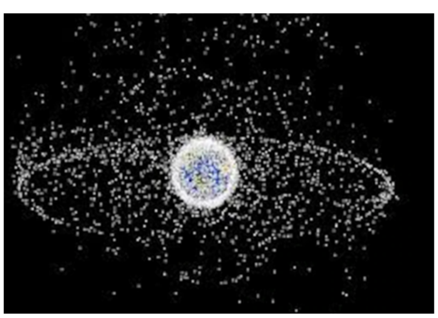


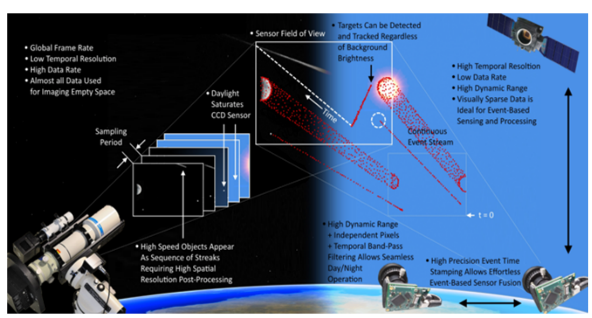
Outline

- EXTRA Framework and Technical Approaches
- Feasibility Test Use Cases
  - Aircraft Maintenance Scheduling
  - Space Situational Awareness
- Future Work and Discussion

Feasibility Test Use Case – Space Domain Awareness

- **Space Situation Awareness (SSA) - detecting, tracking, and identifying objects in orbit**
  - Space domain has become increasingly congested and contested
  - Maintaining space domain awareness is critical
  - Networks of sensors are employed to detect and track resident space objects (RSOs)
  - Need flexible tasking, rapid decision making, and integration between platforms to be effective
  - Complex decision problem cannot be solved with traditional approaches





* https://www.afspc.af.mil/News/Article-Display/Article/1523196/space-situational-awareness-is-space-battle-management/

** https://www.westernsydney.edu.au/icns/research/research_focus/space_situational_awareness_ssa

xxix

Sensor Tasking with XDRL for Space Domain Awareness

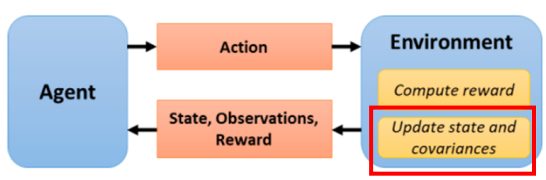
- **Dynamic Sensor Tasking for Space Domain Awareness**
  - ➢ Allocate sensors to resident space objects (RSOs) to improve situation awareness
  - ➢ Large scale optimization problem with complex dynamics and limited resources
  - ➢ Approximate Solution for sequential decision with Deep Reinforcement Learning
  - ➢ Explainable decisions provide confidence for high-stakes autonomous operation

* https://spacenews.com/space-force-reorganizes-former-air-force-space-wings-into-deltas-and-garrisons/

State Observations and Updates

- **For each RSO, the observation actions from the sensors will include the components in the table**
- The environment will behave differently with different choice of actions
- All agents will interact with the environment
  - ➢ Radar can observe both range and angle
  - ➢ EO can only observe angle
  - ➢ Different types of agents (radar and EO) will have different update for the state and covariances (see red box)

Index	Data (Per observation RSO)
1	Elevation of RSO
2	Azimuth of RSO
3	Change of Elevation of RSO
4	Change of Azimuth of RSO
5	Range of RSO (Radar only)
6	Covariance of RSO
7	Distance to the Nearest Critical Asset (e.g., ISS)



xxx

Outline

- ❖ EXTRA Framework and Technical Approaches
- ❖ Feasibility Test Use Cases
- ❖ Future Work and Discussion

Future Works

- **The problems we are working on:**
  - ➢ Build DRL solutions for SSA and AMS problems.
  - ➢ Provide reasons to the human operators about why the RL agent makes the decision.
  - ➢ Explain the intent of the RL agent to the human operators using structure causal model.
  - ➢ Analyze the advantages and disadvantages of each action compared with other choices.

Heterogeneous Data Fusion in B5G IoT Era: (SAS) Sustainability, Accountability, Scalability

Invited Panel: Heterogeneous Data Fusion Learning for Enhanced Xabilities Analysis
The Signal Processing, Sensor/Information Fusion, and Target Recognition XXXI conference
The SPIE Defense + Commercial Sensing

Yu Chen
Dept. of Electrical & Computer Engineering, Binghamton University
Email: ycHen@binghamton.edu

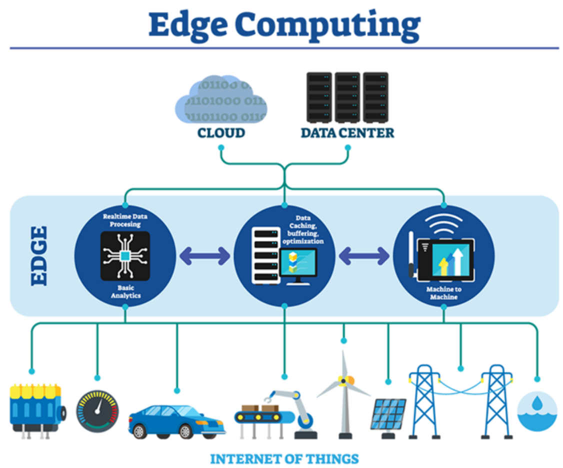
April 04, 2022

BINGHAMTON UNIVERSITY
STATE UNIVERSITY OF NEW YORK

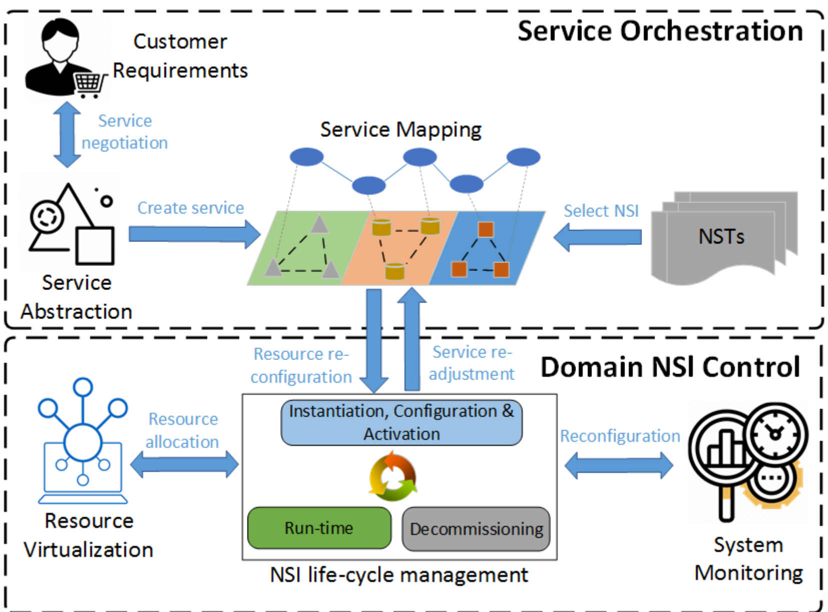
Beyond 5th Generation (B5G) IoT Era: an Application Spectrum

BINGHAMTON UNIVERSITY
STATE UNIVERSITY OF NEW YORK

Example: Pervasive Surveillance in AI/ML Era



BINGHAMTON UNIVERSITY
STATE UNIVERSITY OF NEW YORK



Dynamic

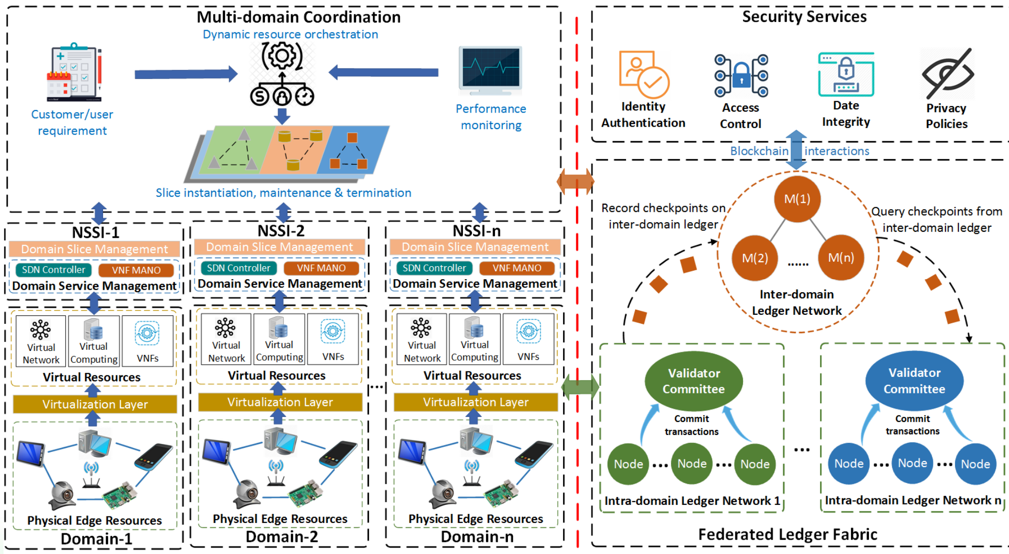
Cross-Domain

Resource

Orchestration

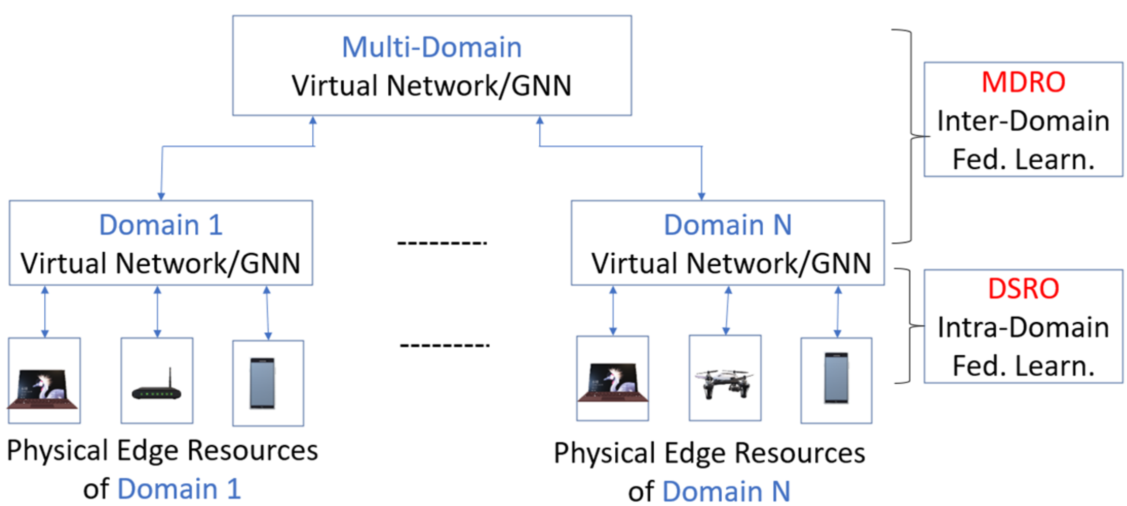
BINGHAMTON UNIVERSITY
STATE UNIVERSITY OF NEW YORK

Multi-Domain Service Coordination on Federated Ledger Fabric



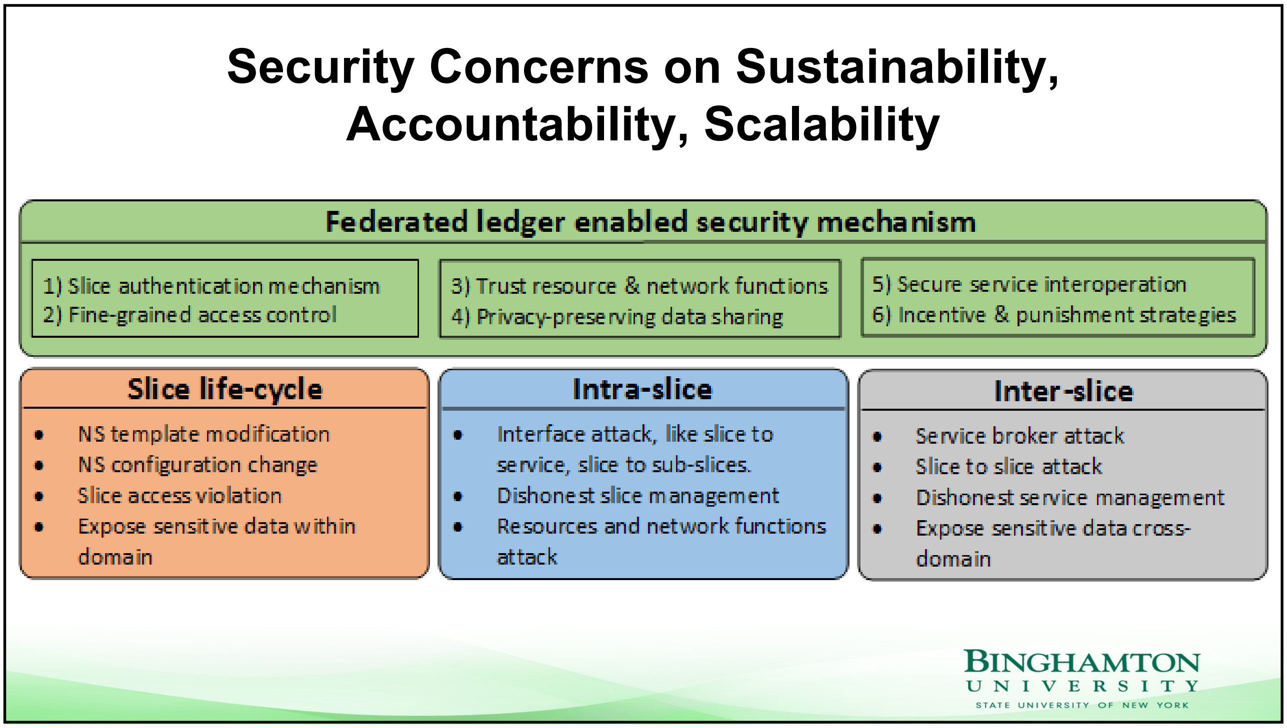
BINGHAMTON UNIVERSITY
STATE UNIVERSITY OF NEW YORK

Multi-Level Federated-Learning Framework



BINGHAMTON UNIVERSITY
STATE UNIVERSITY OF NEW YORK

xxxv


Security Concerns on Sustainability, Accountability, Scalability
Federated ledger enabled security mechanism
1) Slice authentication mechanism
2) Fine-grained access control
3) Trust resource & network functions
4) Privacy-preserving data sharing
5) Secure service interoperation
6) Incentive & punishment strategies
Slice life-cycle
NS template modification
NS configuration change
Slice access violation
Expose sensitive data within domain
Intra-slice
Interface attack, like slice to service, slice to sub-slices.
Dishonest slice management
Resources and network functions attack
Inter-slice
Service broker attack
Slice to slice attack
Dishonest service management
Expose sensitive data cross-domain
BINGHAMTON
UNIVERSITY
STATE UNIVERSITY OF NEW YORK

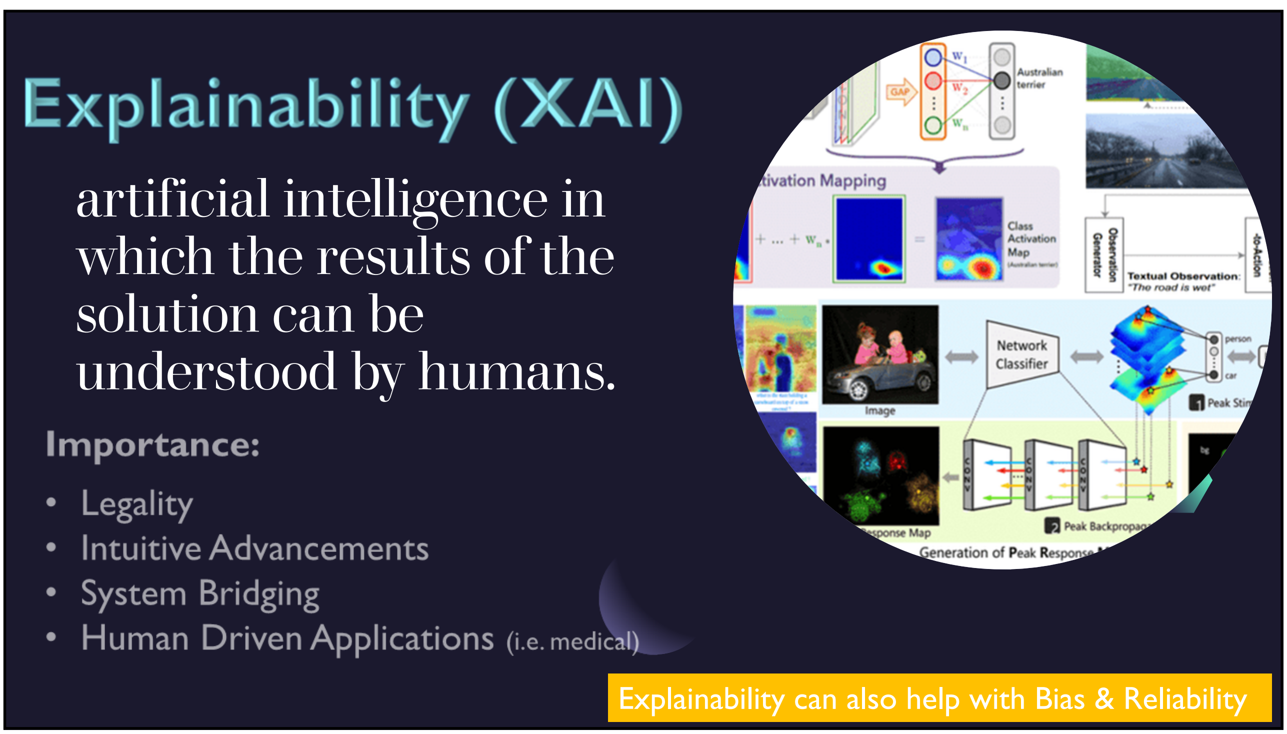
Heterogeneous Data Fusion Learning for Enhanced Xabilities Analysis

Lynne Grewe

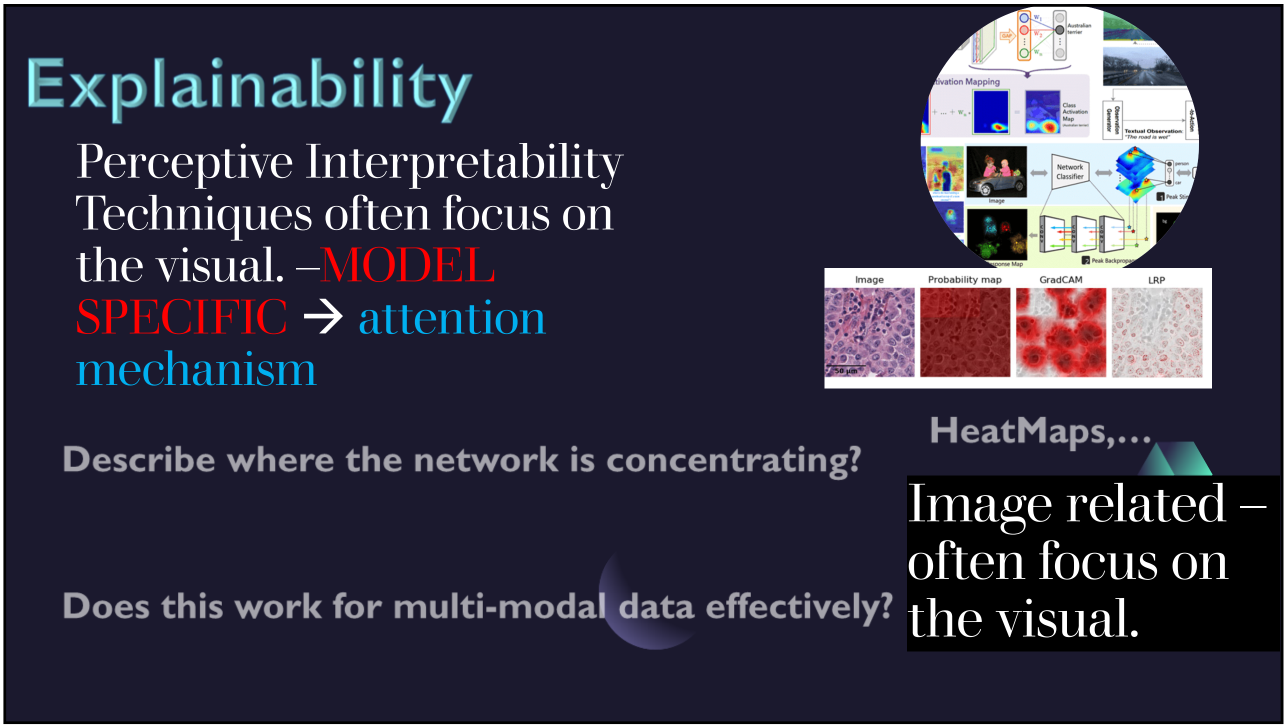
Questions

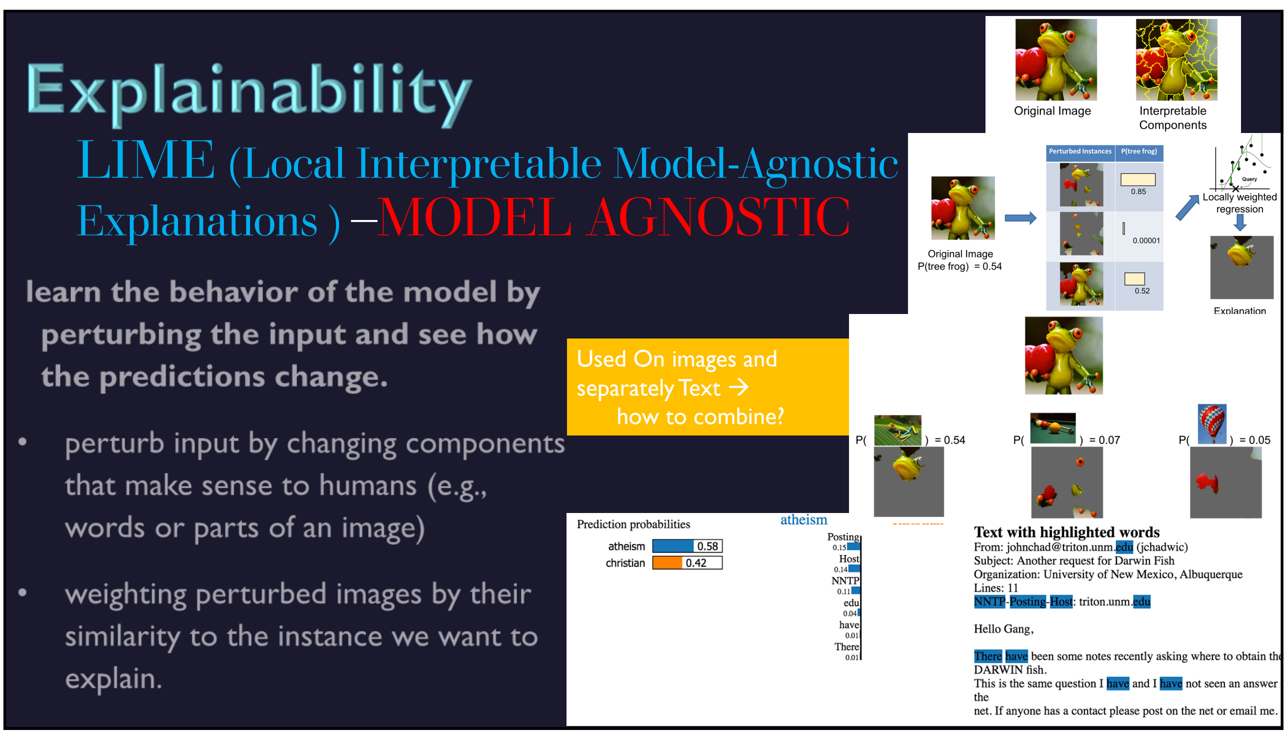
1. Name your top 5 abilities you think are important ?
2. What is the progress for metrics and data fusion?
3. Which "ability" is nice, but not needed?
4. Which "ability" would see progress in the next 5 years of importance for fusionists?


Reliability
Explainability
Accuracy
(test/valid)
Xabilities
"my top 5"
BIAS
Bias
Privacy

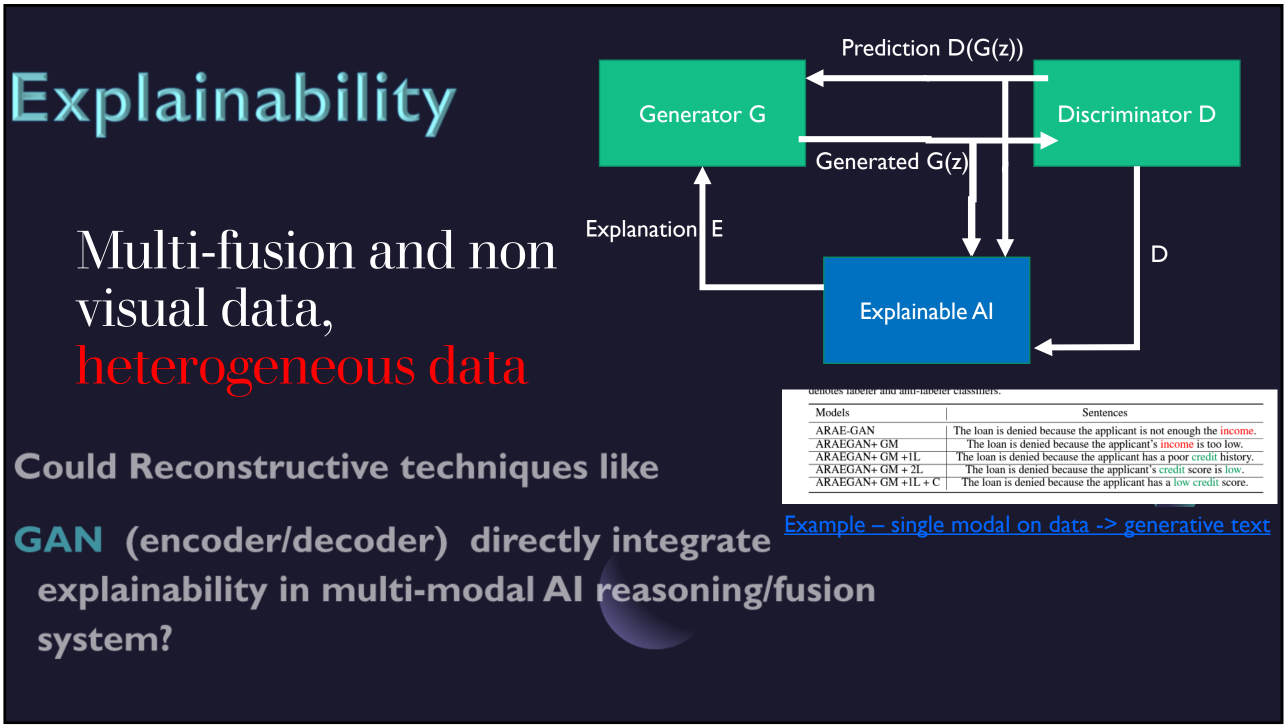

Explainability (XAI)
artificial intelligence in which the results of the solution can be understood by humans.
Importance:
• Legality
• Intuitive Advancements
• System Bridging
• Human Driven Applications (i.e. medical)
Explainability can also help with Bias & Reliability

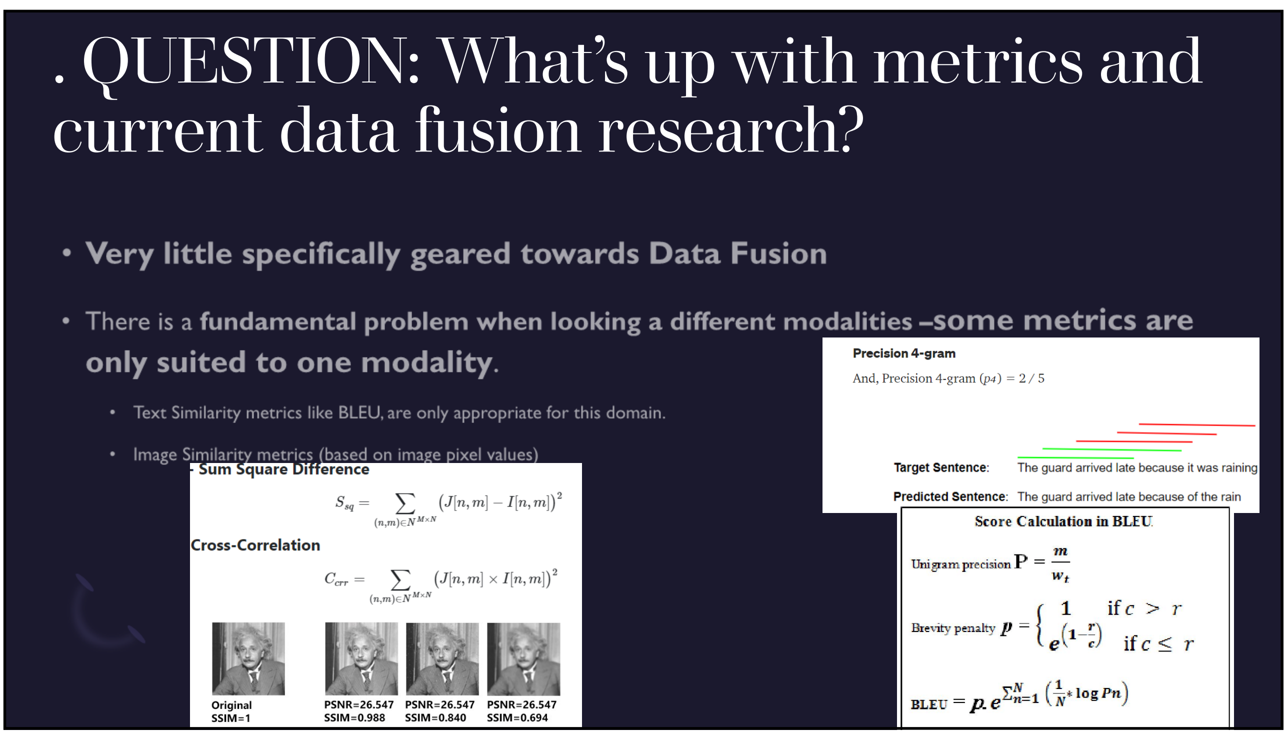
xxxviii


Explainability
Perceptive Interpretability Techniques often focus on the visual. –MODEL SPECIFIC → attention mechanism
Describe where the network is concentrating?
Does this work for multi-modal data effectively?
Image
Probability map
GradCAM
LRP
HeatMaps,…
Image related – often focus on the visual.


Explainability
LIME (Local Interpretable Model-Agnostic Explanations) –MODEL AGNOSTIC
learn the behavior of the model by perturbing the input and see how the predictions change.
• perturb input by changing components that make sense to humans (e.g., words or parts of an image)
• weighting perturbed images by their similarity to the instance we want to explain.
Used On images and separately Text → how to combine?
Original Image
Interpretable Components
Original Image
P(tree frog) = 0.54
Perturbed Instances
P(tree frog)
0.85
0.00001
0.52
Locally weighted regression
Explanation
P( ) = 0.54
P( ) = 0.07
P( ) = 0.05
Prediction probabilities
atheism 0.58
christian 0.42
atheism
Text with highlighted words
From: johnchad@triton.unm.edu (jchadwic)
Subject: Another request for Darwin Fish
Organization: University of New Mexico, Albuquerque
Lines: 11
NNTP-Posting-Host: triton.unm.edu
Hello Gang,
There have been some notes recently asking where to obtain the DARWIN fish.
This is the same question I have and I have not seen an answer the
net. If anyone has a contact please post on the net or email me.

xxxix


Explainability
Prediction D(G(z))
Generator G
Discriminator D
Generated G(z)
Explanation E
D
Explainable AI
Multi-fusion and non visual data, heterogeneous data
Models | Sentences
ARAE-GAN | The loan is denied because the applicant is not enough the income.
ARAEGAN+ GM | The loan is denied because the applicant's income is too low.
ARAEGAN+ GM +1L | The loan is denied because the applicant has a poor credit history.
ARAEGAN+ GM + 2L | The loan is denied because the applicant's credit score is low.
ARAEGAN+ GM +1L + C | The loan is denied because the applicant has a low credit score.
Example – single modal on data -> generative text
Could Reconstructive techniques like
GAN (encoder/decoder) directly integrate explainability in multi-modal AI reasoning/fusion system?


. QUESTION: What's up with metrics and current data fusion research?
• Very little specifically geared towards Data Fusion
• There is a fundamental problem when looking a different modalities –some metrics are only suited to one modality.
• Text Similarity metrics like BLEU, are only appropriate for this domain.
• Image Similarity metrics (based on image pixel values)
- Sum Square Difference
$S_{sq} = \sum_{(n,m)\in N^{M\times N}} (J[n,m] - I[n,m])^2$
Cross-Correlation
$C_{crr} = \sum_{(n,m)\in N^{M\times N}} (J[n,m] \times I[n,m])^2$
Original SSIM=1
PSNR=26.547 SSIM=0.988
PSNR=26.547 SSIM=0.840
PSNR=26.547 SSIM=0.694
Precision 4-gram
And, Precision 4-gram (p_4) = 2 / 5
Target Sentence: The guard arrived late because it was raining
Predicted Sentence: The guard arrived late because of the rain
Score Calculation in BLEU
Unigram precision $P = \frac{m}{w_t}$
Brevity penalty $p = \begin{cases} 1 & \text{if } c > r \\ e^{\left(1-\frac{r}{c}\right)} & \text{if } c \le r \end{cases}$
BLEU $= p.\, e^{\sum_{n=1}^{N}\left(\frac{1}{N} * \log Pn\right)}$

QUESTION: What's up with metrics and current data fusion research?

- **Some metrics like FID (Frechet Inception Distance) can be (modified) used for multiple domains (& can outperform)**

EXAMPLE

- Frechet Inception Distance (FID) for image similarity (input/ generated output GAN /auto encoder-decoder)

Pros and Cons of GAN Evaluation Measures, Ali Borji

FID outperforms BLEU for text generation metric

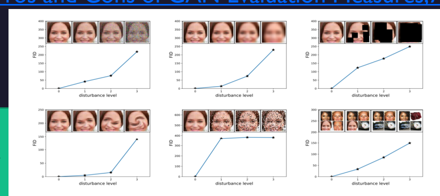


Figure 3: FID is evaluated for **upper left:** Gaussian noise, **upper middle:** Gaussian blur, **upper right:** implanted black rectangles, **lower left:** swirled images, **lower middle:** salt and pepper noise, and **lower right:** CelebA dataset contaminated by ImageNet images. The disturbance level rises from zero and increases to the highest level. The FID captures the disturbance level very well by monotonically increasing.

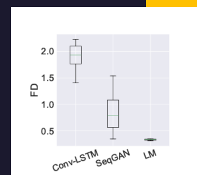


Figure 4: Distributions of FDs achieved by 30 best trials of three different models during hyperparameter search.

Conv-LSTM GAN (BLEU4=0.197, FD=1.464)

a young woman is sitting on a into into, on his sit
young woman woman woman while a group of son
the people are hair with sons
a little girl is wearing dogss
the children is at a red
man man white whiteing

BAD

Language Model (BLEU4=0.204, FD=0.273)

a man is competing in his ski class
the man is playing the accordion
she is the baby's sisters
the man is walking towards the fountain
a boy is climbing a tree lined
a man uses what looks to be a lawn mower

GOOD

Table 1: Random samples from two models with close BLEU scores and considerably different FD.

$\mathcal{N}(\mu, \Sigma)$
distribution of some neural network features of the images generated by the GAN

$\mathcal{N}(\mu_w, \Sigma_w)$
distribution of the same neural network features from the "world" or real images used to train the GAN

$$\mathrm{FID} = ||\mu - \mu_w||_2^2 + \mathrm{tr}(\Sigma + \Sigma_w - 2(\Sigma^{1/2}\Sigma_w\Sigma^{1/2})^{1/2}).$$

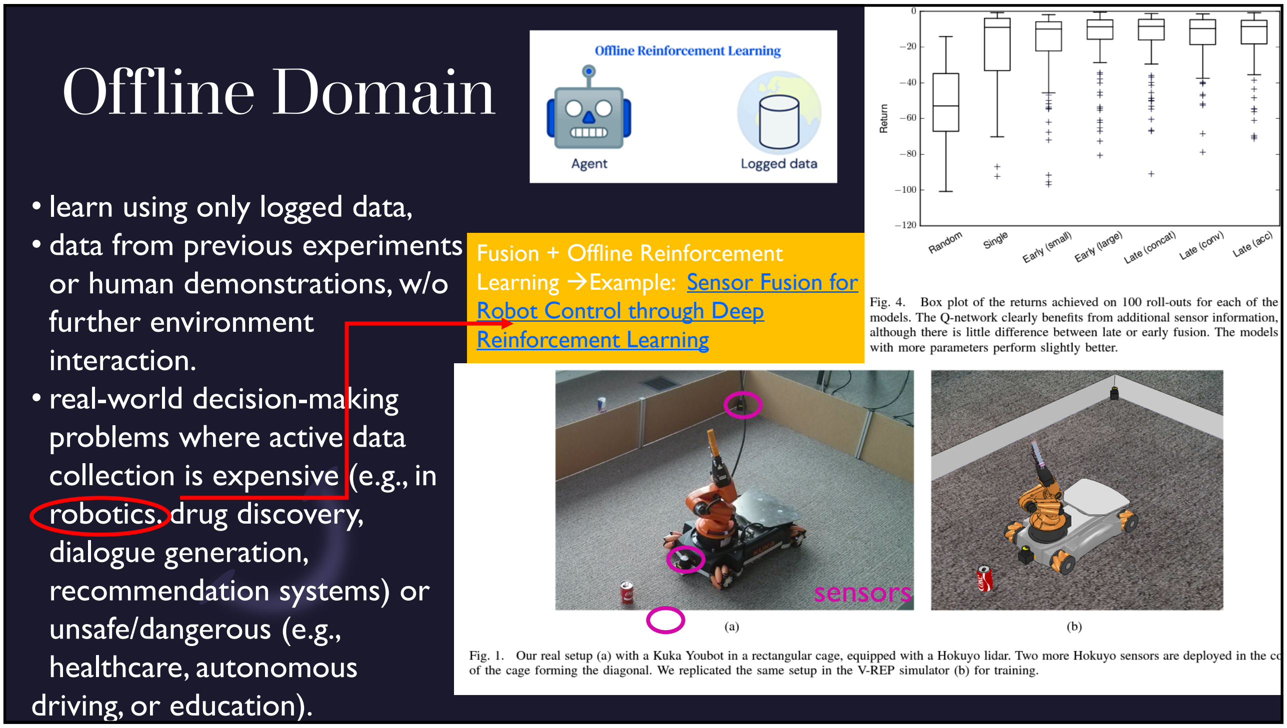
OnAccurate Evaluation of GANs for Language Generation arXiv:1806.04936v3 [cs.CL] 18 Jul 2019, Stanislau Semeniuta, Aliaksei Severyn, Sylvain Gelly

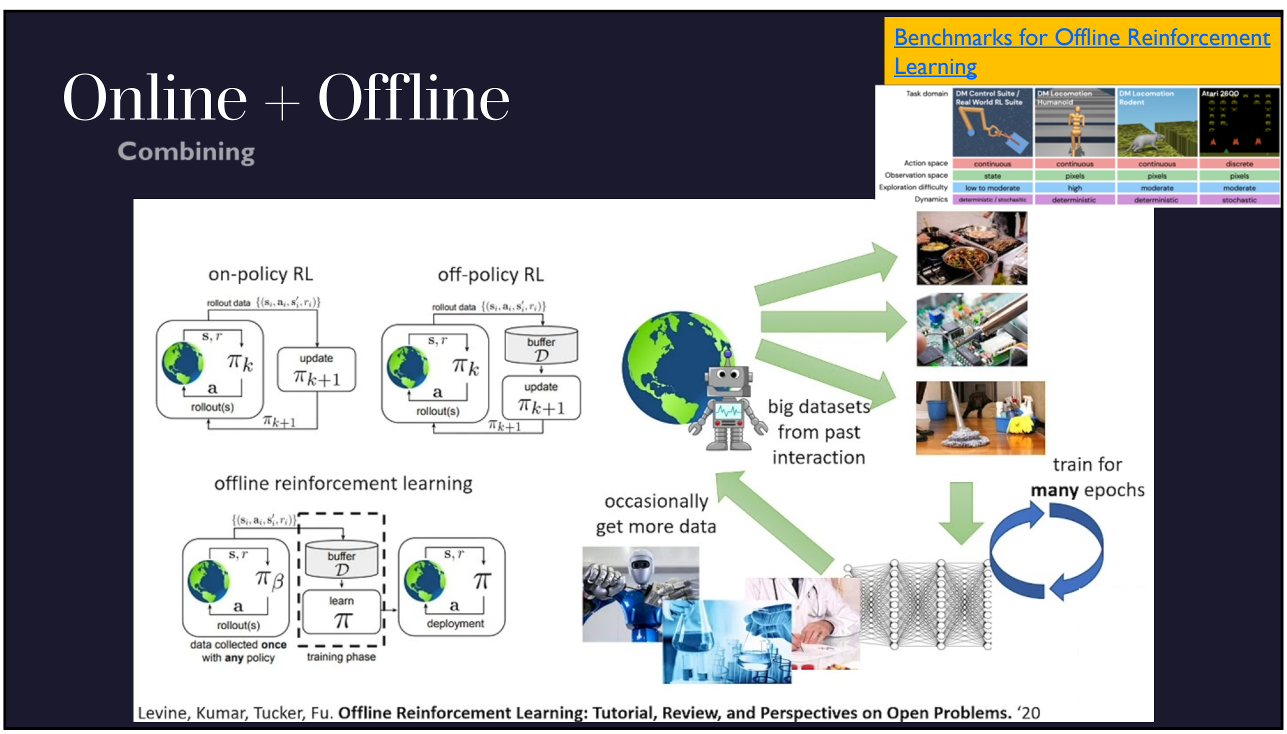
A word about →Domains/learning methods.

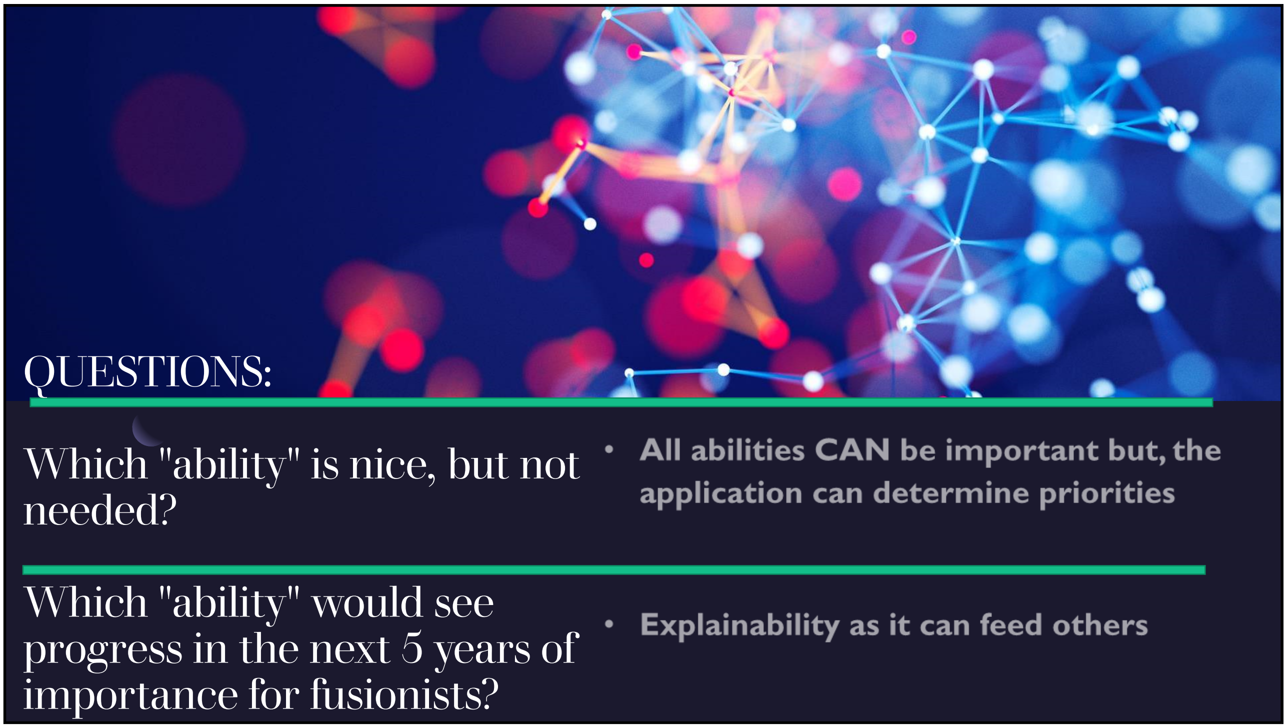
Offline
(static)

Online
(dynamic)

xli


Offline Domain
Offline Reinforcement Learning
Agent
Logged data
• learn using only logged data,
• data from previous experiments or human demonstrations, w/o further environment interaction.
• real-world decision-making problems where active data collection is expensive (e.g., in robotics, drug discovery, dialogue generation, recommendation systems) or unsafe/dangerous (e.g., healthcare, autonomous driving, or education).
Fusion + Offline Reinforcement Learning →Example: Sensor Fusion for Robot Control through Deep Reinforcement Learning
Return
Random
Single
Early (small)
Early (large)
Late (concat)
Late (conv)
Late (acc)
Fig. 4. Box plot of the returns achieved on 100 roll-outs for each of the models. The Q-network clearly benefits from additional sensor information, although there is little difference between late or early fusion. The models with more parameters perform slightly better.
sensors
(a)
(b)
Fig. 1. Our real setup (a) with a Kuka Youbot in a rectangular cage, equipped with a Hokuyo lidar. Two more Hokuyo sensors are deployed in the co
of the cage forming the diagonal. We replicated the same setup in the V-REP simulator (b) for training.


Online + Offline
Combining
Benchmarks for Offline Reinforcement Learning
on-policy RL
off-policy RL
offline reinforcement learning
rollout(s)
update
buffer
learn
deployment
data collected once with any policy
training phase
big datasets from past interaction
occasionally get more data
train for many epochs
Levine, Kumar, Tucker, Fu. Offline Reinforcement Learning: Tutorial, Review, and Perspectives on Open Problems. '20


QUESTIONS:
Which "ability" is nice, but not needed?
All abilities CAN be important but, the application can determine priorities
Which "ability" would see progress in the next 5 years of importance for fusionists?
Explainability as it can feed others

Panel Discussion

Heterogeneous Data Fusion Learning for Enhanced Xabilities Analysis

Andreas Savakis

Rochester Institute of Technology

andreas.savakis@rit.edu

X-abilities Panel

- Xabilities related to Trustworthy AI
  - Analysis over design: Explainability, Interpretability
  - Evaluation: Verifiability, Robustness
  - Test: Validabiliy, Certifiability
  - Deployment: Accountability, Sustainability

- Trustworthy AI attributes
  - NIST Trustworthy AI
  - https://www.nist.gov/programs-projects/trustworthy-and-responsible-ai

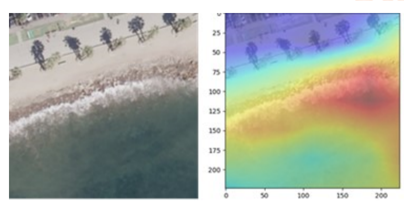
Accuracy
Explainability and interpretability
Privacy
Reliability
Robustness
Safety
Security (Resilience)
Mitigation of harmful bias

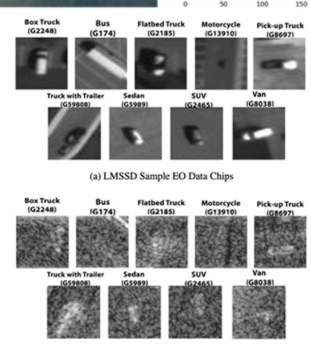
X-abilities: Top 5

1. Evaluation: Verifiability
    - Accuracy
    - Robustness
    - Various conditions
    - New environments
2. Deployment: Accountability
    - Trusted by users
    - Safety: Operates responsibly
    - Efficient operation

X-abilities: Top 5

3. Explain-ability:
    - Interpretable by humans
        - Relatable beyond heatmaps
    -
4. Fairness-ability: No bias
    - Issue in face recognition
    - Fusion datasets can be imbalanced
        - Example of school bus vs military truck
5. Security: Fake Detection Ability
    - Resilience to tampered data
    - Deepfakes affect news, public opinion, politics, decisions





xlvi

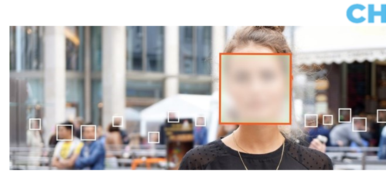
X-abilities: Overlap with current metrics and data fusion research

- Current metrics focus on
  - Accuracy, Image Quality, Perceptual
- New metrics needed for Xabilities as related to human trust of AI:
  - Resilience, Safety, Mitigation of bias
  - Explainability & Interpretability
- Standards: ownership and buy in
  - Engage Professional Societies, Gov, Univ, Industry

X-abilities: “nice” to have

Privacy important for ground-level imagery

- Face redaction
- Removing identifiable information



Privacy for multi-sensor fusion

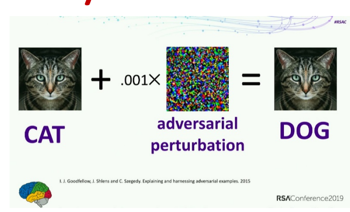
- Aerial imagery over sensitive areas
- More about security than privacy

X-abilities: Progress in the next 5 years

- Data is key: ImageNet scale datasets needed
  - New dataset collection and generation
  - Large multi-modal datasets are becoming available but more annotations are needed
  - Synthetic datasets on the rise
  - Performance gains needed in both accuracy and generalization across datasets

X-abilities: Progress in the next 5 years

- Resilience against attacks
  - Attacks on training datasets
  - Attacks by model tampering
    - Coefficient poisoning
  - Attacks on test imagery
    - Injection of noise artifacts
    - Fake image generation



https://www.theverge.com/2021/4/27/22403741/deepfake
geography-satellite-imagery-ai-generated-fakes-threat