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# Federated Learning for AI and LLMs for Science: Overview of the Activities at the NSF-AI Institute ICICLE

Talk at TPC Track C Workshop (@SC-Asia '24)

by

http://icicle.ai

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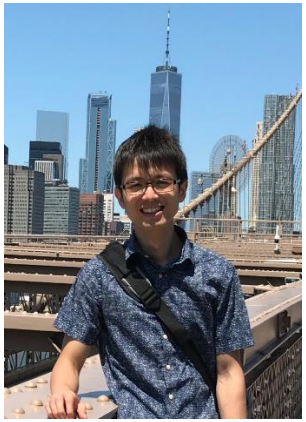
# Credits to all ICICLE Team Members!!

ICICLE Members Attending All-Hands-Meeting In-Person (Nov '23)

# Special Credits (working in Federated Learning)!!



Wei-Lin Chou, Distinguished Assistant Professor of Engineering Inclusive Excellence, Computer Science and Engineering, The Ohio State University

Song Gao, The Ohio State University, Associate Professor, Director of Geospatial Data Science Lab, University Wisconsin-Madison

Yu Su, Distinguished Assistant Professor of Engineering Inclusive Excellence, Computer Science and Engineering, The Ohio State University

Huan Sun, Associate Professor and Endowed CoE Innovation Scholar, Computer Science and Engineering, The Ohio State University

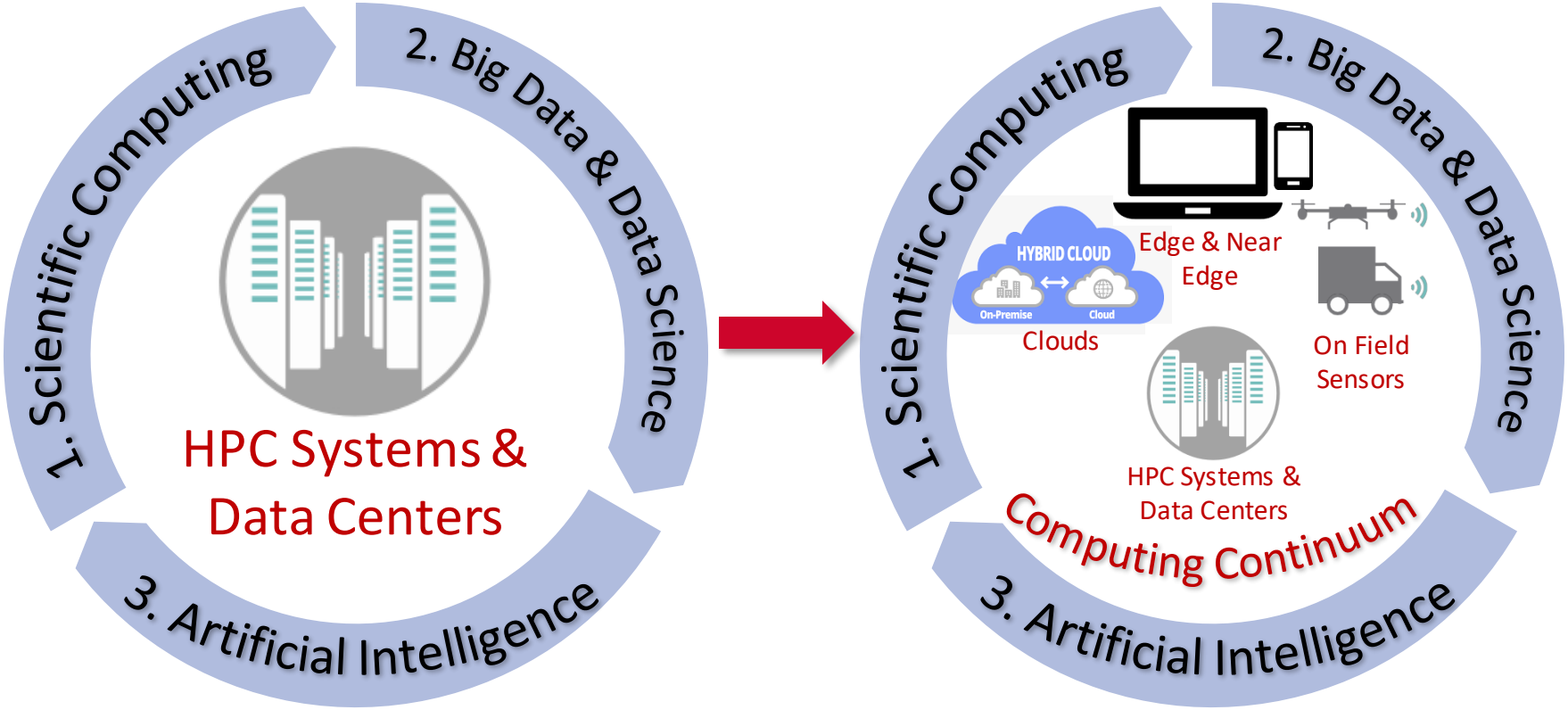
# Outline

- **ICICLE Vision and Goals**
- Research Challenges Addressed
- Highlights of Federated Learning Activities
- How to get engaged?

**Computing** has been evolving over the last three decades with multiple **phases:**

- Phase 1 (1975-): Scientific Computing/HPC
- Phase 2 (2000-): HPC + Big Data Analytics
- Phase 3: (2010-): HPC + AI (Machine Learning/Deep Learning)

# Emergence of the Computing Continuum

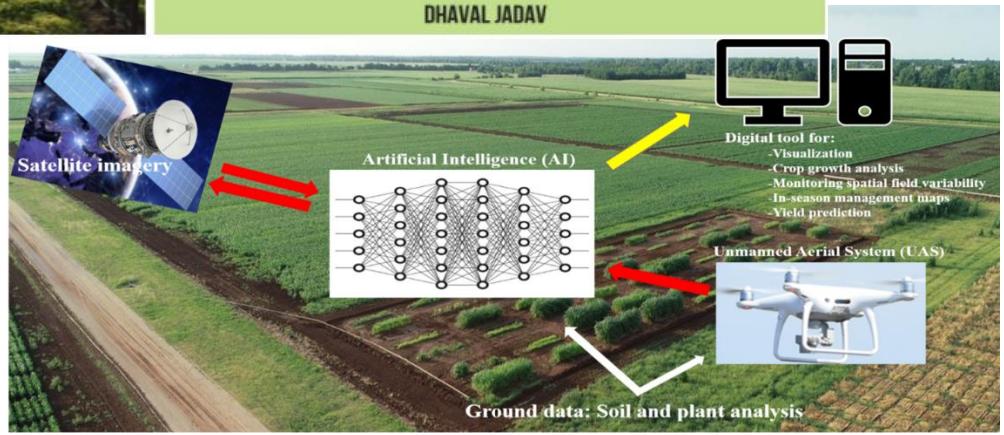


# AI-Driven Digital Agriculture





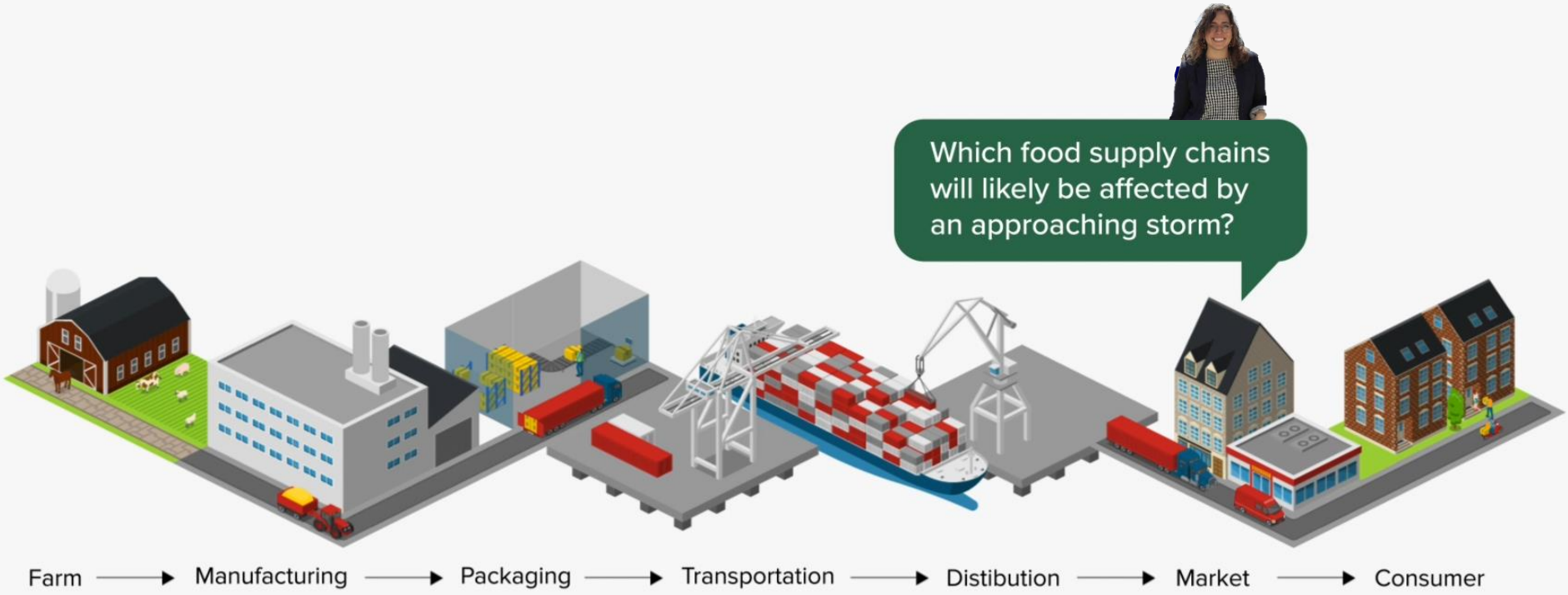



https://ccag.tamu.edu/research-project/digital-agriculture/

https://medium.datadriveninvestor.com/artificial-intelligence-in-agriculture-62f71f8f6ae6

# AI-Driven Foodshed Supply Chain Management?



# AI-Driven Animal Ecology

- **Basic science:** The focus of Animal Ecology is understanding the functioning and behavior of animals individually and in groups *in the context of environment* and evolution.

- **Science + translational:**
  - Monitoring, understanding, and protecting biodiversity of the planet
  - Monitoring and understanding the impact of changing habitats on animals that live in them

- **Translational:** biodiversity conservation and mitigating the impact of climate change

# Broad Challenge

**Designing the next-generation intelligent cyberinfrastructure for a computing continuum with heterogenous resources that is usable in a plug-and-play manner by stakeholders to solve societal challenges?**

# Objectives: Intelligent CyberInfrastructure for Computing Continuum

Use Inspired Science Domains

Digital Agriculture


Smart Foodsheds

Animal Ecology

**ICICLE: Intelligent CyberInfrastructure with Computational Learning in the Environment**

**Systems AI Foundational Research for CI**

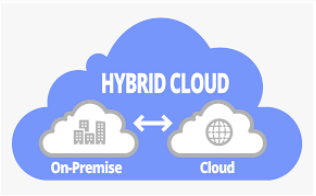
**Intelligent Cyber Infrastructure**

**CI for AI**

**AI for "CI for AI"**

On Field Sensors

Edge & Near Edge




Clouds

HPC Systems & Data Centers

Emerging Computing Continuum

## Participation:

## 14 Organizations, 33 faculty, 41 staff, (58 PhD, 16 MS, 16 undergrad, 6 K-12) students & many Collaborators

**Govt. Agencies & National Labs**

Lawrence Livermore National Laboratory

BROOKHAVEN NATIONAL LABORATORY

Fermilab

**International**

Max-Planck-Gesellschaft

University of Stuttgart Germany

**Industry**

CNH INDUSTRIAL

ADC

WILDME

Microsoft

FARM 2 FACTS

THE FINDINGS GROUP, LLC RESEARCH & EVALUATION

**Research Institutes**

national center for women & INFORMATION TECHNOLOGY

MolSSI

SGCI Science Gateways Community Institute

TRUSTED CI THE NSF CYBERSECURITY CENTER OF EXCELLENCE

ECEP

CAHSI Computing Alliance of Hispanic-Serving Institutions

SCEC AN NSF+USGS CENTER

neon Operated by Battelle

Jetstream

**NSF AI Institutes**

AIFS AI INSTITUTE FOOD SYSTEMS

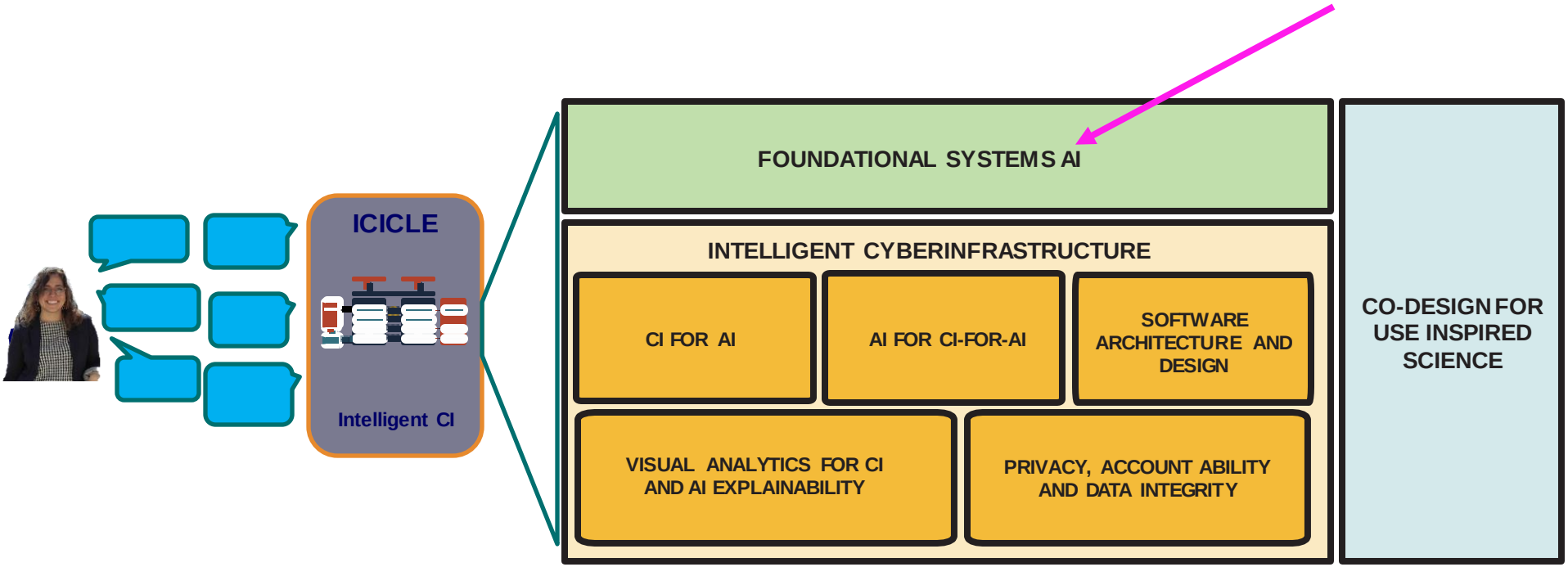
**Hospitals & Universities**

NATIONWIDE CHILDREN'S

# Outline

- ICICLE Vision and Goals
- **Research Challenges Addressed**
- Highlights of Federated Learning Activities
- How to get Engaged?

# Research Plan: Overall Vision



# Thrust: Foundational Systems AI

Components address CI complexity and heterogeneity for plug-and-play

## Knowledge Graphs

- Multimodal KG to encode & reason rich data modalities (e.g., camera trap)
- Auto construction
- Interplay with LLM and knowledge-based QA

## Model Commons

- MINT to support ICICLE use cases, KG, and models
- Precise profiling
- Flex composition
- Versioning and provenance

## Adaptive AI

- Context-aware
- Efficient update
- User-friendly adaptation process
- Adaptation of foundation models, conversational AI

## Federated Learning

- Heterogeneity
- Context-aware
- Privacy-preserving and robustness
- Going beyond classification (GNN, foundation models)

## Conversational AI

- KG- and model-commons-aware
- LLM-powered
- Grounding LLMs to the context
- Hallucination reduction
- Complex reasoning

# Outline

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- **Highlights of Federated Learning Activities**
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# Federated learning (FL) in ICICLE use cases

- Data in **animal ecology**, **digital agriculture**, and **smart foodsheds** are usually collected by individual stakeholders using distributed devices (e.g., drones, camera traps)

Animal Ecology

Digital Agriculture


Smart Foodsheds

- There is a need to **train powerful AI models**, potentially using all the data and available computational resources.
- There is a need for **data privacy, protection, and ownership**.

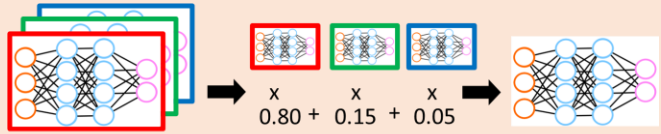
# Focus of ICICLE's federated learning (FL) research

- **A versatile framework to address:**
  - Data heterogeneity (e.g., non-IID distribution) across users
  - Communication constraints
  - Training powerful but deeper models
  - Personalization needs

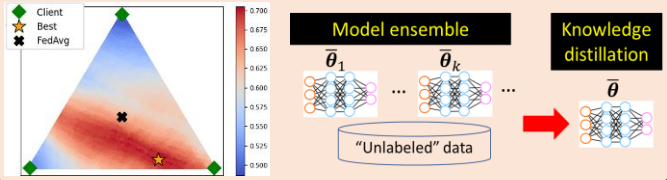
- **Integration with ICICLE use cases:**
  - Visualization and diagnosis
  - Analyzing geospatial resilience of multicommodity food flows
  - Conversational AI parser for effective question-answering
  - Training models for camera traps and digital agriculture

# ICICLE's FL framework

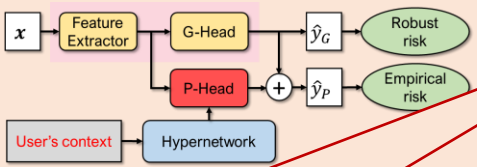
## (7) Efficient adaptation [submitted, IJCAI 24]

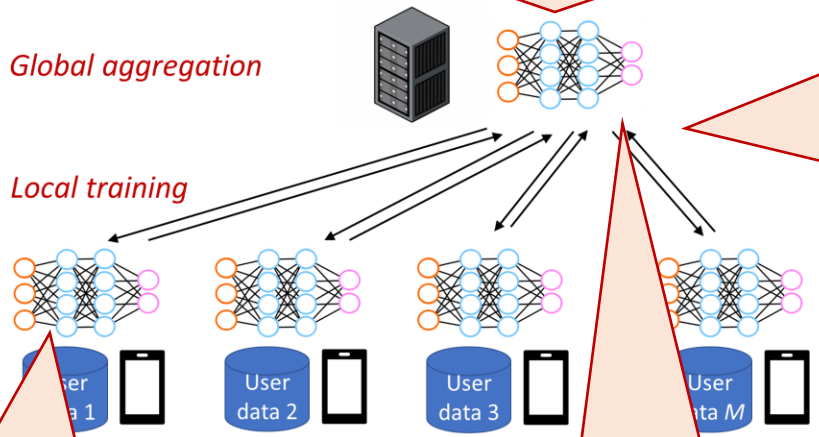



## (1) Bayesian ensemble [ICLR 21]

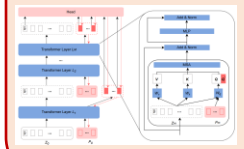



## (2) Decoupled training for personalization [ICLR 22]

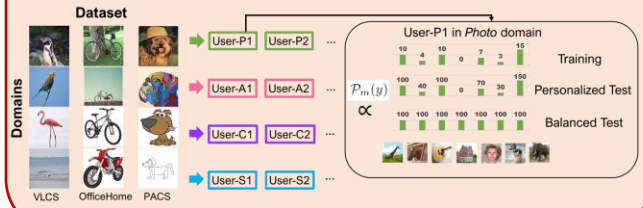


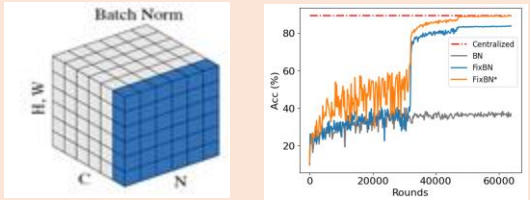

## (5) Efficient update [CVPR 23]



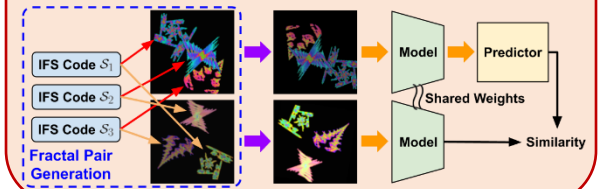
## (6) New benchmarks [submitted, IJCAI 24]




## (3) Fixed BN for training DNNs with BNs in FL [submitted, ICML 24]




## (4) Making pre-training applicable in FL [ICLR 23, AAAI 23]



# Highlight: FixBN for training deeper models in FL

- Our **FixBN** practice makes it possible to train deep neural nets with Batch Normalization (BN) in FL!

Results on CIFAR

| Normalization Layer | Acc (%) |
|---|---|
| BN (Ioffe & Szegedy, 2015) | 53.97 ± 4.18 |
| GN (Wu & He, 2018) | 59.69 ± 0.76 |
| GN +WN (Qiao et al., 2019) | 66.90 ± 0.81 |
| LN (Ba et al., 2016) | 54.54 ± 1.21 |
| IN (Ulyanov et al., 2016) | 59.76 ± 0.43 |
| FIXUP (Zhang et al., 2019) | 70.66 ± 0.24 |
| **FIXBN (Ours)** | **76.56** ± 0.66 |

Results on ImageNet

| Method | Network | Acc. $\Delta_{\text{-BN}}$ |
|---|---|---|
| GN | ResNet18 (He et al., 2016) | 33.33± 0.57 |
| BN | | 48.30± 1.21 |
| **FIXBN** | | **52.43**± 0.68 (+4.1) |

Results on Cityscapes (segmentation)

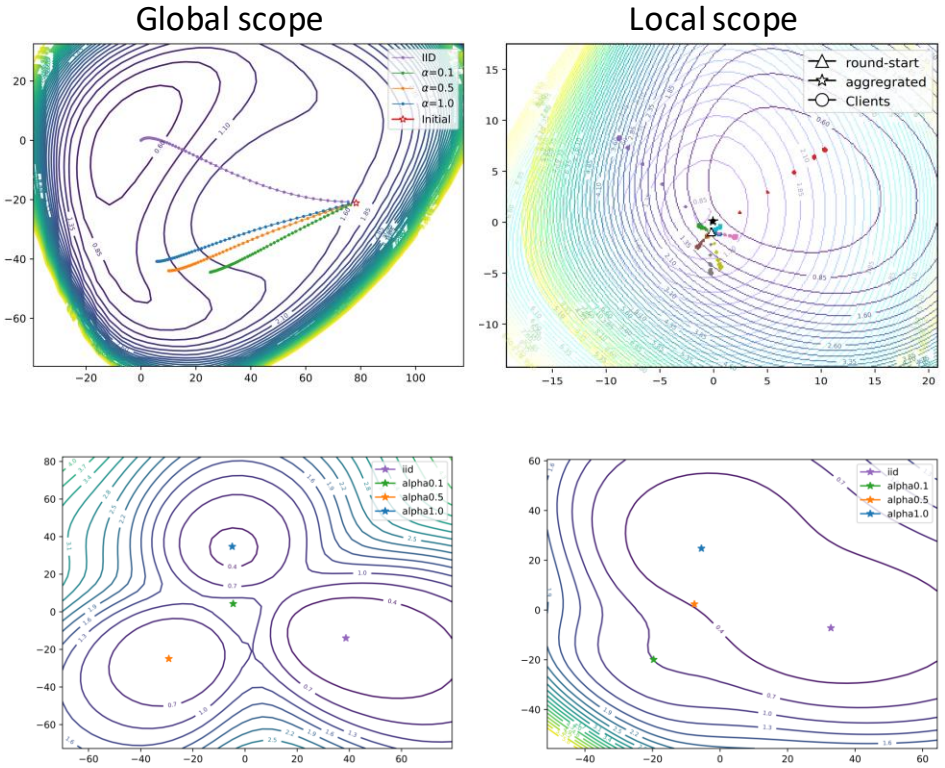
| Method | Backbone | Mean IoU $\Delta_{\text{-BN}}$ |
|---|---|---|
| GN | MobileNet-v2 (Sandler et al., 2018) | 43.2±0.33 |
| BN | | 48.9±0.36 |
| **FIXBN** | | **54.0**±0.29 (+5.1) |
| GN | ResNet50 (He et al., 2016) | 47.8±0.30 |
| BN | | 52.6±0.38 |
| **FIXBN** | | **57.2**±0.32 (+4.6) |

[Making Batch Normalization Great in Federated Deep Learning, arXiv:2303.06530]

# ICICLE's FL visualization tool

- A novel visualization tool to uncover the FL training trajectory, to help users monitor training progress
- The tool leads to new understandings:
  - Pre-training makes FL more robust to data heterogeneity, enabling convergence to the same minima

[Understanding Federated Learning through Loss Landscape Visualizations: A Pilot Study, NeurIPS 2022 Workshop]

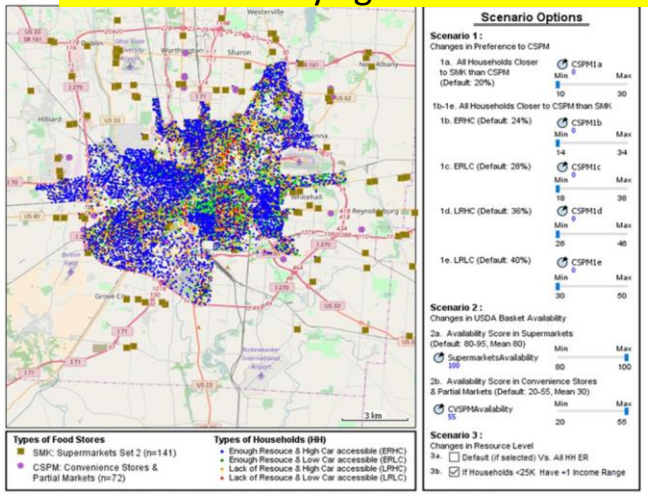


# ICICLE's FL work for the resilience of food flows

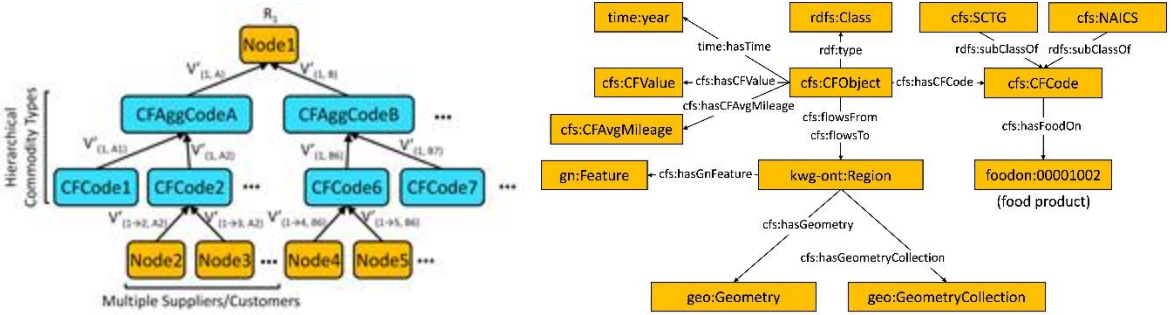
- Understanding and measuring the **resilience of food supply networks** is a global imperative to tackle increasing food insecurity.
- However, the **complexity** of these networks, with their **multidimensional interactions and decisions**, presents significant challenges.

Food supply networks


Food availability agent-based model

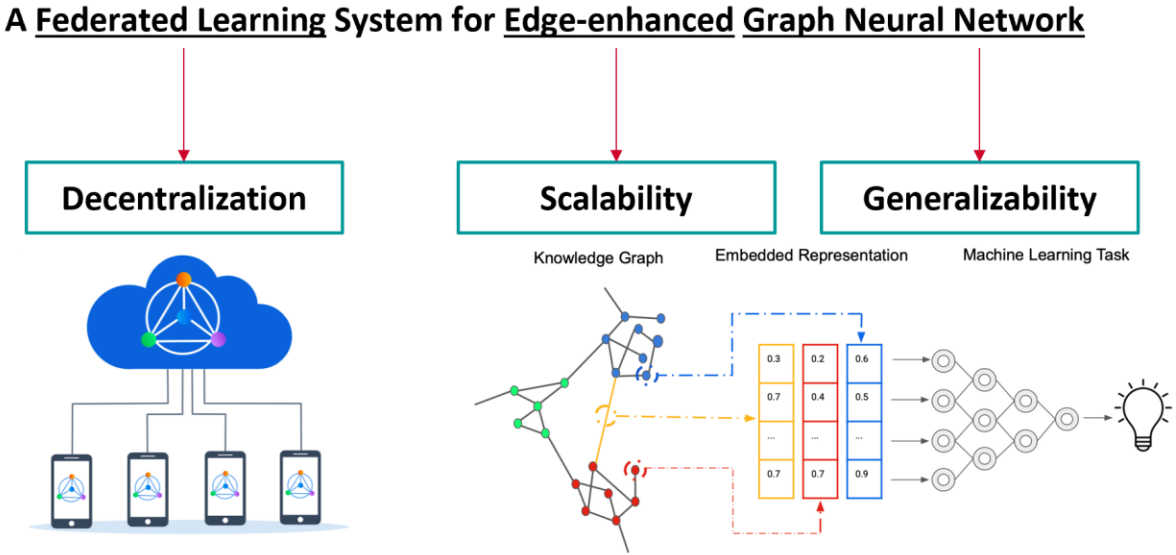



Knowledge graphs



# ICICLE's FL work for the resilience of food flows

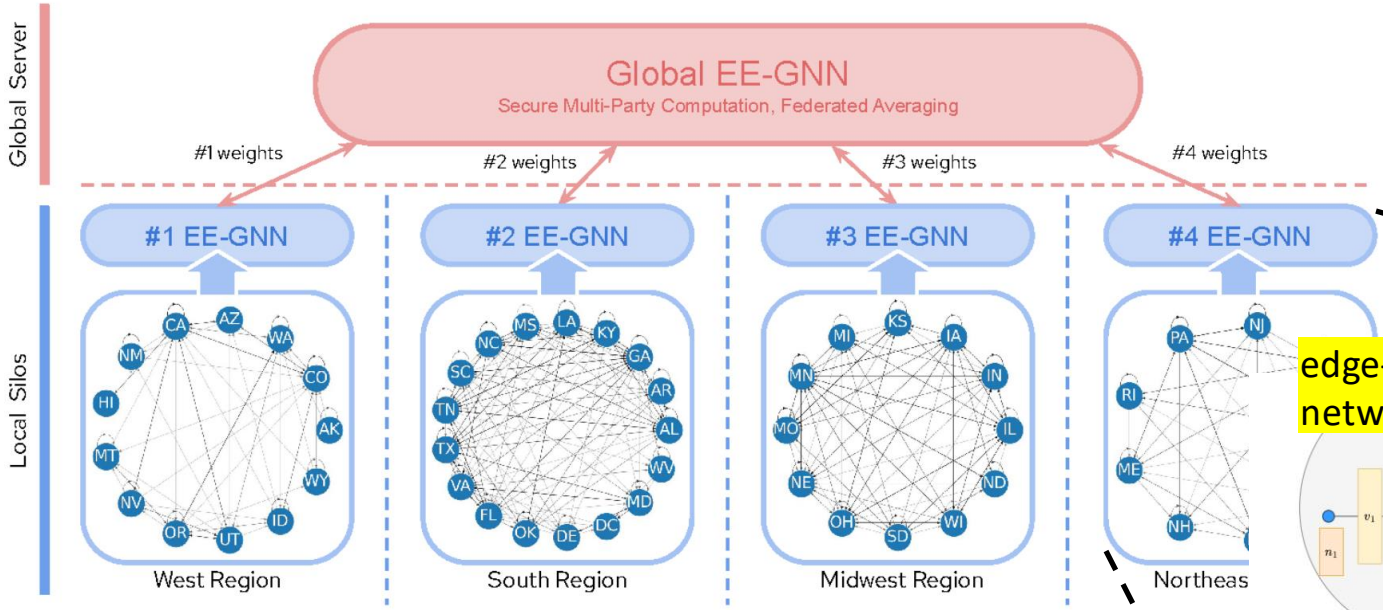
- We propose **FLEE-GNN** to enhance food supply network resilience analysis across geographical regions.
- **FLEE-GNN** combines the robustness and adaptability of GNNs with the privacy-conscious and decentralized aspects of FL.



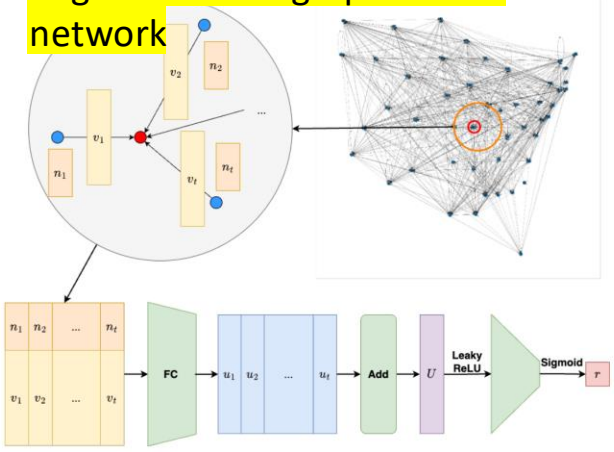

[FLEE-GNN: A Federated Learning System for Edge-Enhanced Graph Neural Network in Analyzing Geospatial Resilience of Multicommodity Food Flows, ACM SIGSPATIAL International Workshop on AI for Geographic Knowledge Discovery]

# ICICLE's FL work for the resilience of food flows

Federated learning architecture for the edge-enhanced graph neural networks



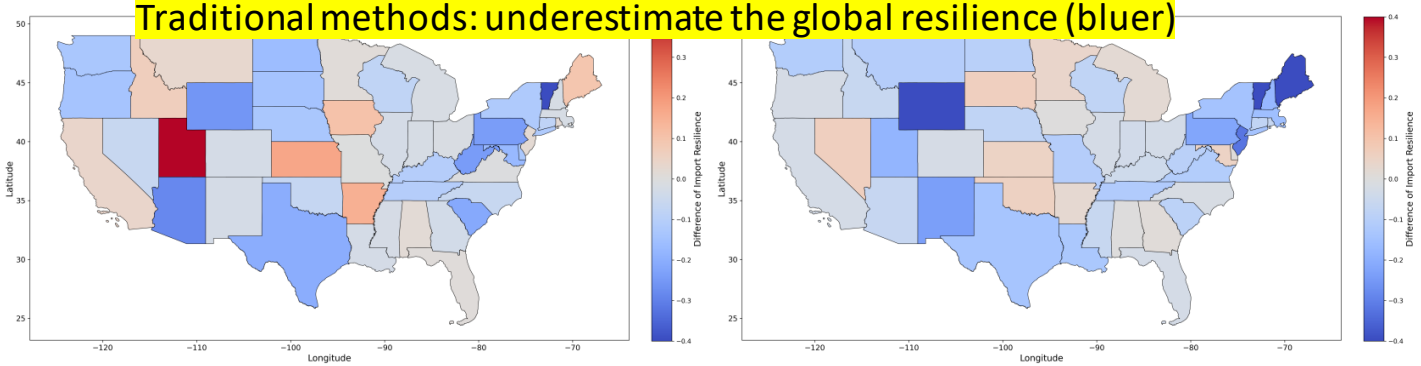

edge-enhanced graph neural network



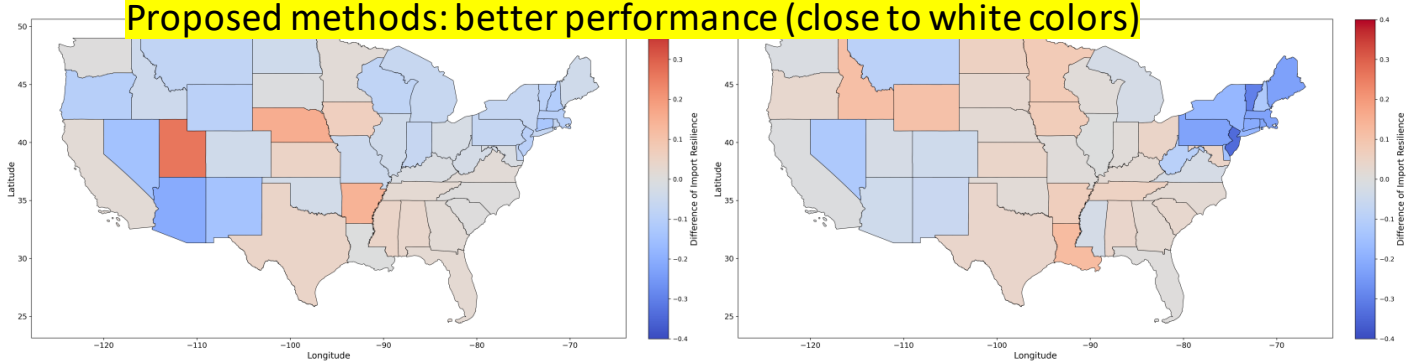

[FLEE-GNN: A Federated Learning System for Edge-Enhanced Graph Neural Network in Analyzing Geospatial Resilience of Multicommodity Food Flows, ACM SIGSPATIAL International Workshop on AI for Geographic Knowledge

# ICICLE's FL work for the resilience of food flows

Traditional methods: underestimate the global resilience (bluer)



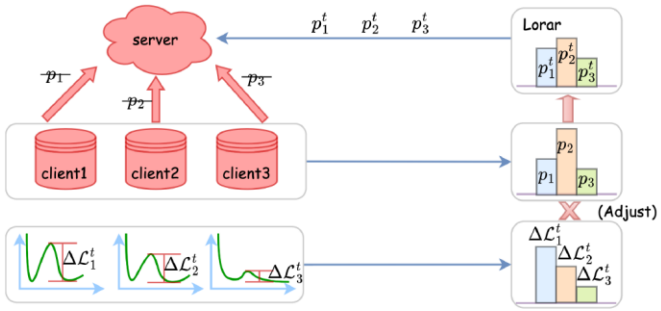

Proposed methods: better performance (close to white colors)




[FLEE-GNN: A Federated Learning System for Edge-Enhanced Graph Neural Network in Analyzing Geospatial Resilience of Multicommodity Food Flows, ACM SIGSPATIAL International Workshop on AI for Geographic Knowledge Discovery]

# ICICLE's federated semantic parsing for QA

## Proposed solutions (Lorar)




For ours (Lorar):

$$p_i^t = |\mathcal{D}_i|\,\Delta\mathcal{L}_i^t / \sum_{i\in C_t} |\mathcal{D}_i|\,\Delta\mathcal{L}_i^t$$

Lorar adjusts each client's contribution to the global model update based on its training loss reduction

## Proposed benchmarks

| | Domain | Train | Dev | Test | SQL Pattern count | Questions / unique query count | Unique tables / query $\mu$ | Unique tables / query Max | SELECTs / query $\mu$ | SELECTs / query Max |
|---|---|---|---|---|---|---|---|---|---|---|
| Advising | Course Infomation | 2629 | 229 | 573 | 174 | 21.7 | 3.0 | 9 | 1.23 | 6 |
| ATIS | Flight Booking | 4347 | 486 | 447 | 751 | 5.6 | 3.8 | 12 | 1.79 | 8 |
| GeoQuery | US Geography | 549 | 49 | 279 | 98 | 3.6 | 1.1 | 4 | 1.77 | 8 |
| Restaurants | Restaurants/Food | 228 | 76 | 74 | 17 | 16.4 | 2.3 | 4 | 1.17 | 2 |
| Scholar | Academic Publication | 499 | 100 | 218 | 146 | 4.2 | 3.2 | 6 | 1.02 | 2 |
| Academic | Microsoft Academic | 120 | 38 | 38 | 92 | 1.1 | 3 | 6 | 1.04 | 3 |
| IMDB | Internet Movie | 78 | 26 | 26 | 52 | 1.5 | 1.9 | 5 | 1.01 | 2 |
| Yelp | Yelp Website | 78 | 26 | 24 | 89 | 1.2 | 2 | 4 | 1 | 1 |

## Improved results

| | Advising† | ATIS† | GeoQuery§ | Restaurants§ | Scholar§ | Academic* | IMDB* | Yelp* | MacroAvg | MicroAvg |
|---|---|---|---|---|---|---|---|---|---|---|
| Finetuning | 84.47 | 53.91 | 72.76 | 98.65 | 74.31 | 57.89 | 26.92 | 33.33 | 62.78 | 71.47 |
| Centralized | 85.51 | 56.38 | 79.21 | 100 | 72.48 | 65.79 | 61.54 | 41.67 | 70.32 | 74.21 |
| FedOPT | 79.76 | 51.23 | **77.42** | **98.65** | **66.51** | 50 | 34.62 | 8.33 | 58.32 | 68.49 |
| FedOPT$_{lorar}$ | **80.98** | **52.35** | 75.99 | **98.65** | 64.68 | **68.42** | **38.46** | **20.83** | **62.55** | **69.39** |
| FedAvg | **76.44** | **50.11** | 59.86 | 72.97 | 38.07 | 2.63 | 7.69 | 12.5 | 40.03 | 57.89 |
| FedAvg$_{lorar}$ | 74.69 | 49.89 | **68.82** | **98.65** | **52.29** | **65.79** | **46.15** | **25** | **60.16** | **63.91** |
| FedProx | **74.52** | **50.56** | 65.95 | 81.08 | 38.53 | 10.53 | 3.85 | 8.33 | 41.67 | 58.84 |
| FedProx$_{lorar}$ | 73.12 | 49.66 | **67.38** | **98.65** | **48.17** | **63.16** | **46.15** | **20.83** | **58.39** | **62.42** |

[Federated Learning for Semantic Parsing: Task Formulation, Evaluation Setup, New Algorithms, ACL 2023]

# Reference


- On the Importance and Applicability of Pre-Training for Federated Learning, ICLR 2023
- Visual Query Tuning: Towards Effective Usage of Intermediate Representations for Parameter and Memory Efficient Transfer Learning, CVPR 2023
- Federated Learning for Semantic Parsing: Task Formulation, Evaluation Setup, New Algorithms, ACL 2023
- FLEE-GNN: A Federated Learning System for Edge-Enhanced Graph Neural Network in Analyzing Geospatial Resilience of Multicommodity Food Flows, ACM SIGSPATIAL Workshop 2023
- Federated Learning of Shareable Bases for Personalization-Friendly Image Classification, arXiv:2304.07882
- Making Batch Normalization Great in Federated Deep Learning, arXiv:2303.06530
- On Bridging Generic and Personalized Federated Learning for Image Classification, ICLR 2022
- Understanding Federated Learning through Loss Landscape Visualizations: A Pilot Study, NeurIPS 2022 Workshop
- FedBE: Making Bayesian model ensemble applicable to federated learning, ICLR 2021

# Outline

- ICICLE Vision and Goals
- Research Challenges Addressed
- Highlights of Federated Learning Activities
- **How to get Engaged?**

# Multiple Levels of Collaboration and Engagement

- Using the Released Software/CI components
  - Available at https://icicle.osu.edu/cyberinfrastructure/software
  - Get engaged as a member in the Stakeholder Roundtable (more details below)
- Become a part of ICICLE (multiple options)
  - Student Associate
  - Visiting Research Fellow
  - Academic Collaborator
  - Industry Partner
  - Stakeholder Roundtable Member
  - More details at: https://icicle.osu.edu/engagement/join-us
- Join the ICICLE mailing lists (https://icicle.osu.edu/engagement/mailing-lists)
  - icicle-announce
  - icicle-discuss

# An Expanded Presentation on ICICLE

# Keynote Talk in the

# AI-driven Infrastructure Track
# Room C3.2
# 1:30 pm (Today, 02/21/24)

# Acknowledgments to all ICICLE Participants (Faculty, Students and Staffs)


***Current Faculty***

- E. Ayday, CWRU
- V. Chaudhary, CWRU
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- C. Stewart, OSU
- Y. Su, OSU
- H. Subramoni, OSU
- H. Sun, OSU
- C. Stewart, RPI
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- M. Norman, UC San Diego

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- M. Baghini, IITB
- Chalapathi G, IITB
- A. Sinha, IITB
- R. Velmurugan, IITB
- S. Paramane, TIH IITB

***Current International Students TIH - IITB***

- A. Borkar, TIH IITB
- RM. Chitre, TIH IITB
- R. Katole, TIH IITB
- S. Khandelwal, TIH IITB
- T. Sharma, TIH IITB
- A. Thaduri, TIH IITB
- S. Zac, TIH IITB

***Current K-12 Students***

- R. Estanislao, SDSC
- D. Lee, SDSC
- M. Ray, SDSC
- S. Samar, SDSC

***Past K-12 Students***

- J. Karpinski, SDSC
- A. Sarin, SDSC

***Past Masters Students***

- SR. Kalli, OSU
- H. Panday, OSU
- RR. Loka, UW Madison
- D. Sykes, UW Madison

***Current Ph.D. Students***

- P. Kousha, OSU
- Z. Li, OSU
- V. Pahuja, OSU
- R. Qiu, OSU
- E. Romero, OSU
- C. Tu, OSU
- Y. Tu, OSU
- S. Vallabhajosyula, OSU
- L. Waltz, OSU
- B. Wang, OSU
- X. Wang, OSU
- J. Yao, OSU
- X. Yue, OSU
- T. Zhang, OSU
- K. Zhang, OSU
- Z. Zhang, OSU
- DD. Vecchia, RPI
- M. Rosas, UD
- T. Jiang, UU
- Y. Xu, UU
- J. Yan, UU
- K. Armendariz, UW-Madison
- J. Rao, UW-Madison
- J. Kline, OSU
- G. Ubbiali, IC-Foods

***Current Institute Evaluators (WFD)***

- T. McKlin, TFG
- C. Wise, TFG

***Current Masters Students***

- R. Danhi, IC-Foods
- J. Cheng, OSU
- S. Deshmukh, OSU
- M. Han, OSU
- A. O'Quinn, OSU
- C. Wang, OSU
- J. Yang, OSU
- Q. Ding, TACC
- V. deBella, UW Madison
- M. Krempely, UW Madison
- S. Suresh, UW Madison
- G. Wilkins, UW Madison

***Current Undergraduate Students***

- T. Chen, OSU
- KA. Irizarry, OSU
- M. Lieber, OSU
- E. Luo, OSU
- D. Venkataraman, OSU
- S. Shah, UT Austin
- A. Karunakaran, UW Madison
- M. Kuhn, UW Madison
- Y. Qu, UW Madison
- K. Sung, UW Madison

***Educational Fellows (2023)***

- B. Alston, OSU
- TE. Feiten, UC
- A. Hingle, GMU
- C. Lucken, UC
- C. Okolo, CU

***Past UG Students***

- S. Ockerman, OSU
- KP. Sailaja, OSU
- C. Washington, OSU
- J.Kim, TACC
- C. Skevofilax, TACC
- S. Wegner, UW Madison

# Thank You!