# Defense Presentation

# Synergies of Mean-field Games in Machine Learning and 6G Communication Networks

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# Outline

- **Introduction**
  - Mean-field Game
- Work 1: Time Efficient Offloading Optimization in Automotive Multi-Access Edge Computing Networks Using Mean-Field Games
- Work 2: Task Selection and Route Planning for Mobile Crowd Sensing Using Multi-Population Mean-Field Games
- Work 3: MFG Augment: Data augmentation using Mean-field Games
- Work 4: Joint Server Selection and Handover Design for Satellite-Based Federated Learning Using Mean-field Evolutionary Approach
- Conclusion & Future Work

# Introduction (1/4) – Mean-field Game (MFG)

- What is Mean-field Game (MFG):

A model to study the group behavior for a large-population system by utilizing the group states distribution. By modeling the group behavior, the system model will be simplified significantly.

xample: Fish C

Reef fish swimming like hurricane

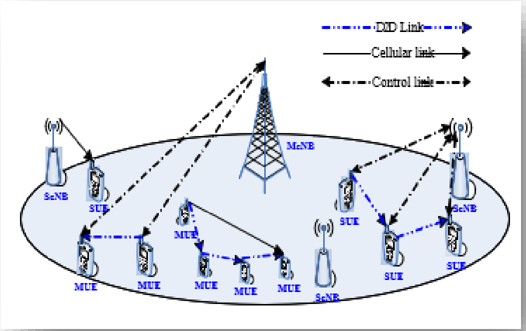
Sheep running in fear of a drone

# Introduction (2/4) – Mean-field Game (MFG)

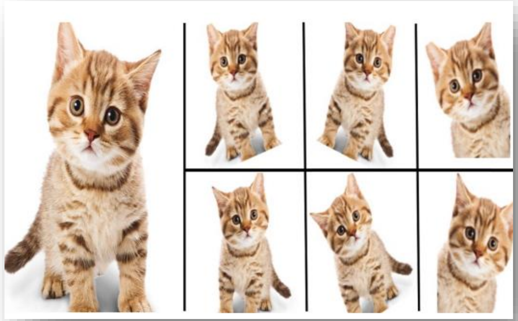
❑ MFG Applications

UAVs control

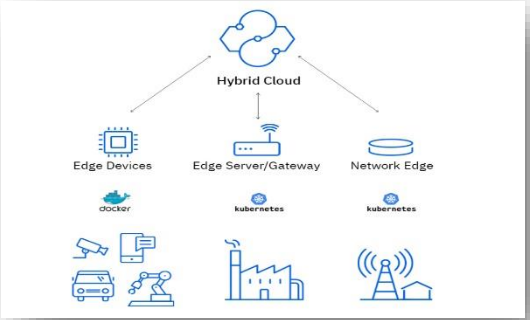
Robots Path Planning




Power Control in Ultra-Dense D2D Networks



Data Augmentation




Edge Computing


Epidemic Model

# Introduction (3/4) – Mean-field Game (MFG)

- MFG: Combination of Optimization and Game Theory

**Optimization Problem**

$$\underset{u\in\mathcal{U}}{\text{minimize}} \quad J(u)$$

**Game Theory**

$$\underset{u_i\in\mathcal{U}_i}{\text{minimize}} \quad J_i(u_i, \mathbf{u}_{-i})$$

**Optimal Control Problem**

$$\underset{u\in\mathcal{U}}{\text{minimize}} \quad J(u)$$
$$\text{subject to} \quad \dot{x} = f(t, x, u)$$

**Differential Game**

$$\underset{u_i\in\mathcal{U}_i}{\text{minimize}} \quad J_i(u_i, \mathbf{u}_{-i})$$
$$\text{subject to} \quad \dot{x} = f(t, x, u_i, \mathbf{u}_{-i})$$

**Mean Field Game**

$$\underset{u\in\mathcal{U}}{\text{minimize}} \quad J(u, \rho)$$
$$\text{subject to} \quad \dot{x} = f(t, x, u, \rho, W)$$

$J$ = Cost function
$x$ = State variable
$u$ = Agent $i$'s Control
$\mathrm{u}_{-i}$ = Control set of all the other agents besides agent $i$
**$\rho$ = Mean field**
$W$ = Stochastic Drift

# Introduction (4/4) – Mean-field Game (MFG)

## MFG Mathematical Format:

$$\underbrace{\min_{\alpha(t)}}_{\text{Agent's Strategy}} J_k = \mathbb{E}\left[\int_0^T \underbrace{\boxed{L(\alpha(t), X^k(t), \rho(t))\, dt}}_{\text{Agent's Running cost}} + \underbrace{\boxed{G(X^k(T), \rho(T))}}_{\text{Agent's Terminal cost}}\right],$$

$$\text{s.t.} \quad \underbrace{\partial_t \rho}_{\text{Agent state distribution}} - \underbrace{\nu \Delta \rho}_{\text{Drift term}} + \nabla \cdot \underbrace{(\rho f)}_{\text{Interaction term}} = 0 \longrightarrow \text{Agent Population's Dynamics}$$

$$\underbrace{\rho(x,0) = \rho_0(x),}_{\text{Agent Population's Initial States Distribution}}$$

**Bellman Optimality Principle**

$$v(x,t) = \inf_{u \in \mathcal{U}} J(u,m)$$

↓

**HJB**

$$-\partial_t v + H(x, D_x v, D^2_{xx} v, m) = 0$$

$v(x,t)$ → FPK

**FPK**

$$\partial_t m + \mathrm{div}(f(x,v)m) = \frac{1}{2}\partial^2_{xx}((\sigma^\top \sigma)_{i,j} m),$$

$m(x,t)$ → HJB

↑

$$[x_1(t), \ldots, x_N(t)] \rightarrow m(x,t)$$

**Mean Field Approximation**

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- Work 3: MFG Augment: Data augmentation using Mean-field Games
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- Conclusion & Future Work

# Work I: MFG for Edge Computing Fast Offloading

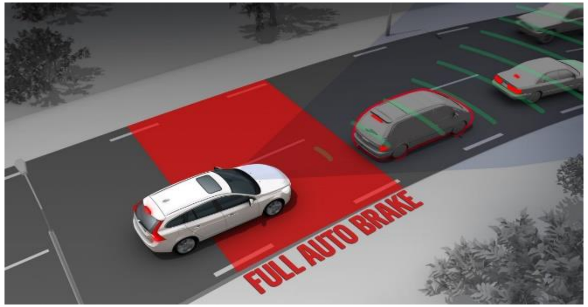
## Motivation: Background of Vehicular Edge Computing (VEC)

VEC is a paradigm that an edge server perform data processing tasks for nearby vehicles. This releases high computation load of vehicles, speeds up response times, enhances data processing.

TOYOTA InfoTech
*Envisioning Mobility*

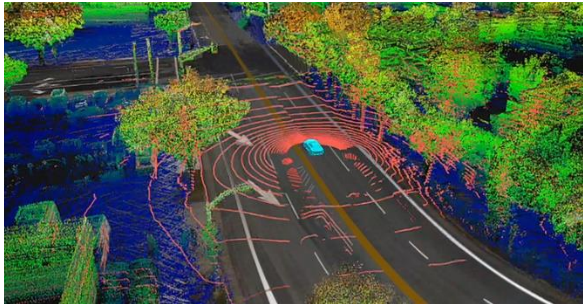
Intersection safety warning

- The environment information is dynamic and need to be offloaded timely.




Emergency electronic brake

- Time latency sensitive
- Transmission & Computation sensitive



High Definition (HD) Map

- Data size of a 3D HD map will be 375 EB/month.

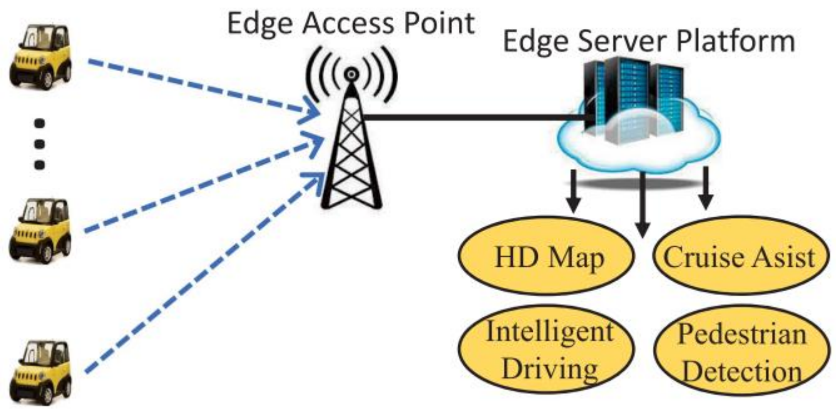
# Work I: MFG for Edge Computing Fast Offloading

- Motivation: Why MFG?

  - ✗ Improving the data offloading performance (e.g., latency, energy efficiency, etc.) for time-sensitive vehicular applications is a key challenge faced by current VEC.
  - ✗ The computation time (training time) of existing offloading mechanism is long, and can not meet vehicles’ latency requirement when the number of vehicles is large.
  - ✓ MFG is able to reduce the computation complexity and therefore reduce latency.

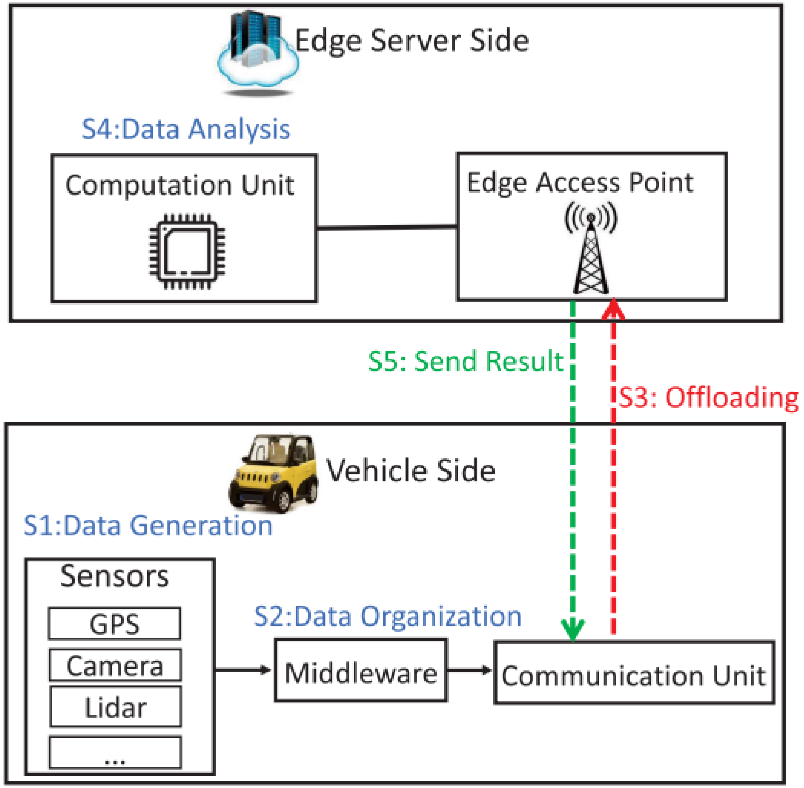
# Work 1: MFG for Edge Computing Fast Offloading

- System Model:




- Vehicles are equipped with sensors: GPS, Camera, Lidar, etc.
- EAP connect with edge server through optical fiber.

- Workflow of Edge Tasks:



# Work I: MFG for Edge Computing Fast Offloading

- Problem Formulation: Offloading Optimization

1. Vehicles' Average Data Transmission Energy Consumption:

$$\bar{J}_1 = \mathbb{E}_{x\sim\rho}\left[\int_0^T c_1 \frac{u(t)^2}{g} dt\right] = \int_0^T \int_\Omega c_1 \frac{u(t,x)^2}{g} \rho(t,x) dx dt,$$

Data rate

Channel gain between vehicle and access point

Distribution of vehicles' remaining data size

2. Vehicles' Averaged Computation energy consumption of Edge Tasks

$$\bar{J}_2 = \mathbb{E}_{x\sim\rho}\left[c_2 k f^2 (s_n - x_n(T))\right] = \mathbb{E}_{x\sim\rho}\left[\int_0^T c_2 k f^2 u(t) dt\right]$$

$$= \int_0^T \int_\Omega c_2 k f^2 m(t,x) dx dt.$$

Task Size

Size of task remained at vehicle side at final time

- $x\epsilon[0,B]$ is the size of data to be offloaded,
- $\Omega$: Space of data size
- $t \in [0,T]$ is time
- $T$ is the time latency requirement of edge tasks

- $k$: A constant depending on CPU architecture
- $f$: CPU frequency of the edge server
- $m = \rho * u$: An intermediate term

# Work I: MFG for Edge Computing Fast Offloading

## Problem Formulation: Offloading Optimization

3. Vehicles' Averaged Task Latency Cost:

We hope that at the required final time, all vehicles finish offloading all its task-related data.

$$\bar{J}_3 = \mathbb{E}_{x\sim\rho}\left[c_3 \underbrace{x(T)}_{\text{Size of task remained at vehicle side at required final time}}{}^2\right] = \int_\Omega c_3 x^2 \rho\underbrace{(T,x)}_{\text{Distribution of vehicles remaining data size at required final time}} dx,$$

# Work I: MFG for Edge Computing Fast Offloading

- Problem Formulation: MFG Data Offloading Problem

$$\mathcal{P}_2 : \inf_{\rho,m} J = \underbrace{\boxed{\int_0^T \int_\Omega c_1 \frac{m(t,x)^2}{\rho(t,x)g} dxdt}}_{\text{Transmission Energy}} + \underbrace{\boxed{\int_0^T \int_\Omega c_2 k f^2 m(t,x) dxdt}}_{\text{Computation Energy}} + \underbrace{\boxed{\int_\Omega c_3 x^2 \rho(T,x) dx}}_{\text{Task Latency Cost}}.$$

$$s.t. \begin{cases} \mathcal{C}_1 : \partial_t \rho(t,x) - \nabla \cdot (m(t,x)) = 0, & \longrightarrow \text{Task Offloading Dynamics} \\ \mathcal{C}_2 : \rho(0,x) = \rho_0, & \longrightarrow \text{Task sizes distribution} \\ \mathcal{C}_3 : u_n(t) = B\log_2\left(1 + \frac{p_n(t)g}{\sigma_n^2}\right), & \longrightarrow \text{Data rate} \end{cases}$$

# Work I: MFG for Edge Computing Fast Offloading

## G-prox PDHG Algorithm:

- Step 1: Define the Lagrangian function $L$ by introducing a dual variable $\Phi$.

- Step 2: Solve the saddle-point Lagrangian problem.

- Step 3: Iteratively update the strategy $m$, state distribution $\rho$, dual variable $\Phi$, and terminal distribution $\rho_T$ for all populations

**Algorithm 1** G-prox PDHG algorithm for the multi-population mean-field game

Initialize $\rho_n$, $m_n$ and $\phi_n$ for $i = 1, 2, \ldots, N_1$, $j = 1, 2, \ldots, N_2$, and $l = 1, 2, \ldots, N_3$, according to (37). Random initialize $\rho_n^T$ for $i = 1, 2, \ldots, N_1$, and $j = 1, 2, \ldots, N_2$. $K = 1$.
**while** $k \leqslant K$ **do**
  **for** $n = 1, 2, \cdots, N$ **do**
    **for** $i = 1, 2, \ldots, N_1$ **do**
      **for** $j = 1, 2, \ldots, N_2$ **do**
        **for** $l = 1, 2, \ldots, N_3$ **do**
          Update $\rho_n$, $m_n$, $\phi_n$ and $\rho_n^T$ according to (43), (45), (46), and (49) respectively;
        **end for**
      **end for**
    **end for**
  **end for**
**end while**
**return** : Optimal value of $\rho_n^*(t, x)$ and $m_n^*(t, x)$, $\forall n \in \{1, 2, \cdots, N\}$.

# Work I: MFG for Edge Computing Fast Offloading

## G-prox PDHG Algorithm:

- Step 1: Define the Lagrangian function $L$ by introducing a dual variable $\Phi$.
- Step 2: Solve the saddle-point Lagrangian problem.

**Algorithm 1** G-Prox PDHG Algorithm

$$
\begin{aligned}
\rho^{k+1} &= \arg\min_{\rho}\left(\mathcal{L}(m^k,\rho,\Phi^k) + \frac{1}{2\tau}\|\rho-\rho^k\|^2_{L^2(\Omega\times[0,1])}\right)\\
m^{k+1} &= \arg\min_{m}\left(\mathcal{L}(m,\rho^{k+1},\Phi^k) + \frac{1}{2\tau}\|m-m^k\|^2_{L^2(\Omega\times[0,1])}\right)\\
\Phi^{k+1} &= \arg\max_{\Phi}\left(\mathcal{L}(2m^{k+1}-m^k, 2\rho^{k+1}-\rho^k,\Phi) - \frac{1}{2\sigma}\|\Phi-\Phi^k\|^2_{H^1(\Omega\times[0,1])}\right).
\end{aligned}
$$

# Work I: MFG for Edge Computing Fast Offloading

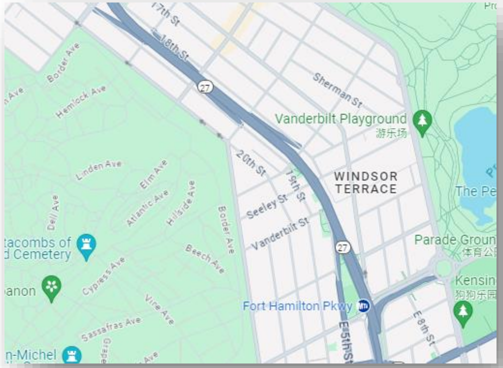
## Simulation Result:

- Parameter Settings:

Vehicles task size: A Gaussian Distribution [0.6 – 0.8] MB

TABLE II
PARAMETERS FOR SIMULATION

| Parameters | Values |
|---|---|
| Number of vehicles $N$ | $1 \sim 100$ |
| Transmission cost coefficient $c_1$ | $10^{-6}$ |
| CPU structure constant $k$ | $1 \times 10^{-18}$ |
| Computation cost coefficient $c_2$ | $0.01 \times 10^{-18}$ |
| CPU frequency $f$ | 3.0 GHz |
| Latency cost coefficient $c_3$ | 500 |
| Latency requirement $T$ | 1 s |
| G-prox PDHG algorithm step size $\tau$, $\sigma$ | 0.1, 1 |
| Channel gain $g$ | -60db |
| Discretization size $N_1$, $N_2$ | 40 |

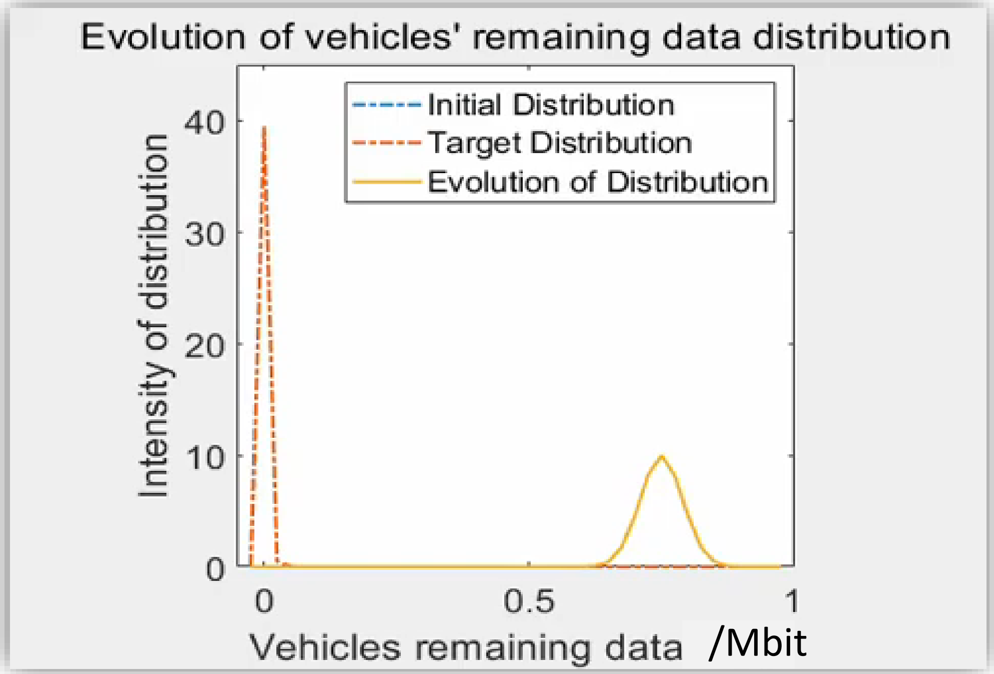



**Brooklyn Traffic**

# Work I: MFG for Edge Computing Fast Offloading

## Simulation Result:

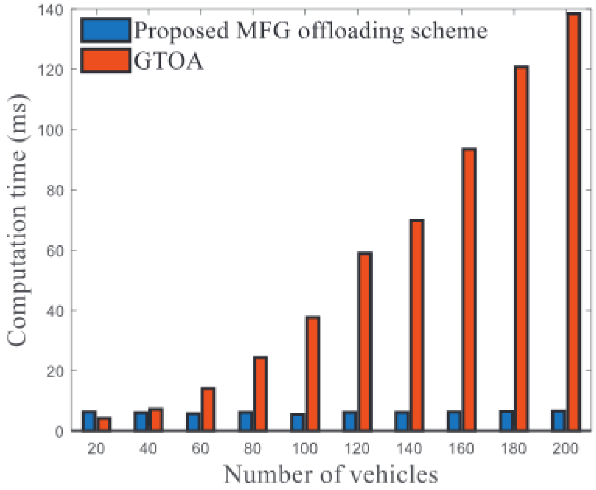
- Evolution of distribution of vehicles' remaining task size:

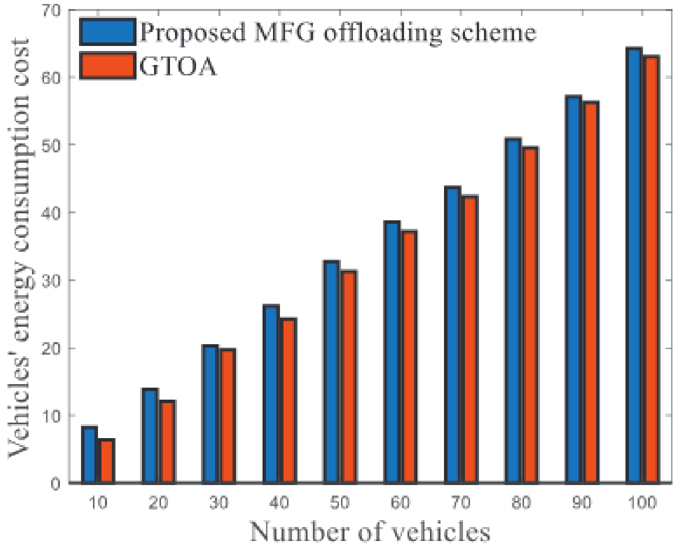


# Work I: MFG for Edge Computing Fast Offloading

## ☐ Simulation Result:

### ■ Code Running Time Analysis




- GOTA: A well adopted game−theoretic computation offloading algorithm
- Code running time of proposed MFG scheme is independent of the number of vehicles
- Reduce code running time about 95% for 200 vehicles

- Achiever similar optimized costs

# Work I: MFG for Edge Computing Fast Offloading

- Simulation Result: Brooklyn Bridge Traffic Data:

Edge server coverage area

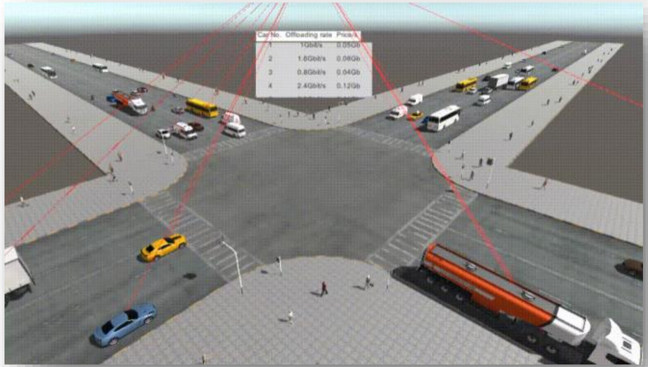
● Vehicle

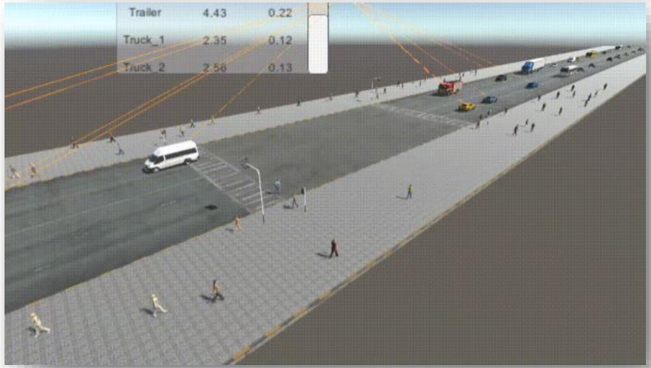
● Vehicle meets the latency requirement

● Vehicle can't meet the latency requirement

Proposed solution

Traditional solution





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# Work 2: MFG for Mobile Crowd Sensing

## ☐ Motivation: Why Mobile Crowd Sensing (MCS)?

The Mobile crowd sensing (MCS) is a new paradigm that takes advantage of pervasive mobile devices to efficiently collect data, enabling numerous large-scale applications.

Agriculture Monitoring

GPS


Human body Monitoring

# Work 2: MFG for Mobile Crowd Sensing

## Motivation: Why Mobile Vehicles?

- High mobility
- Fast and flexible deployment
- Large service coverage
- Powerful on-board CPU


UAV

Tesla Vehicle with Autopilot

Package delivering


Hollywood filming

Mobile vehicles in MCS!

Sensing

# Work 2: MFG for Mobile Crowd Sensing

☐ Motivation: Why MFGs?

✓ Q1: How to control a large number of vehicles?

We Propose:

Task Selection and Route Planning for Mobile Crowd Sensing

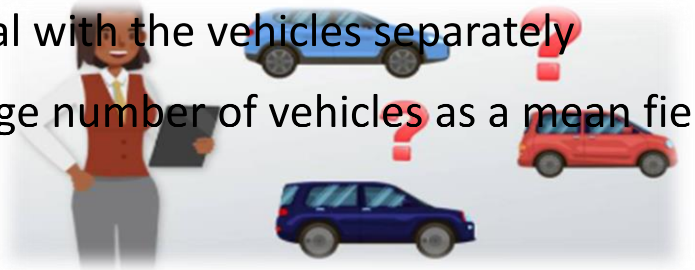
Using Multi-Population Mean-Field Games

✓ Q2: How to save energy?


☒ Other games: high computational complexity - - deal with the vehicles separately

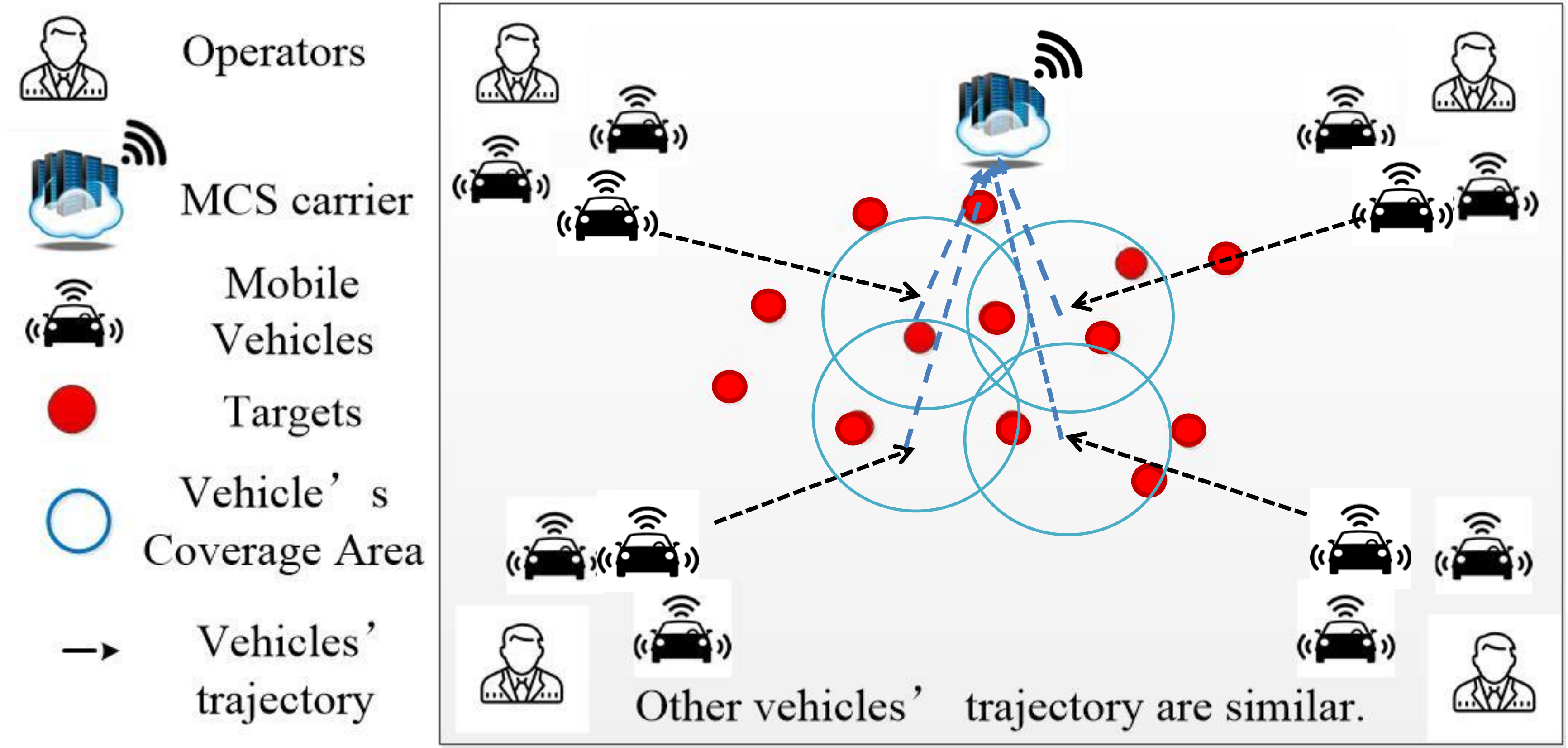
☑ Mean field game: low complexity - - regard the large number of vehicles as a mean field

✓ Q3: How to make task select decision for large number of vehicles and their owners?



# Work 2: MFG for Mobile Crowd Sensing

- Conceptual illustration



# Work 2: MFG for Mobile Crowd Sensing

- Problem Formulation： A joint task selection and path planning problem

1. Average energy consumption of vehicles：

Momentum: $m = \rho * v.$

$$\bar{J}_1 = \int_0^T \int_\Omega \frac{1}{2}\rho(t,x)\|v(t,x)\|_2^2 \, dxdt = \int_0^T \int_\Omega \frac{\|m(t,x)\|_2^2}{2\rho(t,x)} dxdt$$

Sensing area

Distribution of vehicles.

- $v$ is the velocity of vehicles
- $x$ is the location of vehicles

2. Obstacle collision cost:

$$\bar{J}_2 = \mathbb{E}_{x(t)\sim\rho(t)}\left[\int_0^T \lambda(x)dt\right] = \int_0^T \int_\Omega \rho(t,x)\lambda(x)dxdt,$$

where $\lambda(x)$ is defined as

Collision economic cost

$$\lambda(x) = \begin{cases} \lambda, x \in O_x, \\ 0, x \notin O_x, \end{cases}$$

$O_x$ is the set of obstacles position

# Work 2: MFG for Mobile Crowd Sensing

## Problem Formulation:

3. Reward paid by the MCS carrier:

The expected number of targets that UAVs covers.

Operators' competition

$$\boxed{\frac{\rho_n(T,x)}{\sum_{i=1}^{N}\rho_i(T,x)}}$$

Operators are competing against others!

$$\bar{J}_3 = -c_1 \int_{\Omega} \int_{\boxed{\|z-x\|_2 \leqslant r_0}} \boxed{\rho(T,x)}\, \rho_T(z) e^{-k_0\|z-x\|_2} dz dx \Rightarrow \tilde{J}_3 = -c_1 \int_{\Omega} \int_{\|z-x\|_2 \leqslant r_0} \rho_T(z) \frac{\rho_n(T,x)}{\sum_{i=1}^{N}\rho_i(T,x)} e^{-k_0\|z-x\|_2} dz dx$$

Final distribution of Vehicles

Targets distribution

$r_0$ is the radius of vehicles' sensing area

Assumption:

- If two UAVs senses the same target, the profit will be shared evenly.

# Work 2: MFG for Mobile Crowd Sensing

## Problem Formulation:

4. Maximum Achievable Uplink Multiple Access Channel Capacity:
For Additive White Gaussian Noise (AWGN) Channel

$$\bar{J}_4 = -c_2 \int_\Omega \rho(T,x) B\log_2\left(1 + \frac{P\eta\|x - x_0\|_2^{-\gamma}}{N_0 B}\right) dx,$$

- $B$ is the channel bandwidth,
- $x_0$ the location of the MCS carrier
- $P_i$ is the transmitted signal power,
- $N_0$ is the AWGN power spectral density,
- $\eta$ is a unified constant depends of the channel attenuation,
- $\gamma$ is the path loss exponent.

# Work 2: MFG for Mobile Crowd Sensing

- Problem Formulation: Over all Multi-population MFG problem (For one operator)

$$\mathcal{P}_2: \inf_{\rho, m} \; J = \int_0^T \int_\Omega \frac{\|m(t,x)\|_2^2}{2\rho(t,x)} + \rho(t,x)\lambda(x)\,dx\,dt$$ → Energy Consumption + Collison Cost

$$-c_1 \int_\Omega \int_{\|z-x\|_2 \leqslant r_0} \rho_T(z) \frac{\rho_n(T,x)}{\sum_{i=1}^{N} \rho_i(T,x)} e^{-k_0\|z-x\|_2}\,dz\,dx.$$ → Profit

$$-c_2 \int_\Omega \rho(T,x) B \log_2\left(1 + \frac{P\eta\|x-x_0\|_2^{-\gamma}}{N_0 B}\right) dx.$$ → Channel capacity

$$s.t. \; \begin{cases} \mathcal{C}_5: \partial_t \rho(t,x) + div(m(t,x)) = 0, \\ \mathcal{C}_6: \rho(0,x) = \rho_0, \end{cases}$$

$\mathcal{C}_5$ → Liouville Equation: How vehicle state population moves based on velocity (Newton's law)

$\mathcal{C}_6$ → Vehicles' initial distribution

# Work 2: MFG for Mobile Crowd Sensing

## G-prox PDHG Algorithm for multi-population MFG problem:

- Step 1: Define the Lagrangian function $L_i$ by introducing a dual variable $\Phi_i$.
- Step 2: Solve the saddle-point Lagrangian problem.
- Step 3: Iteratively update the strategy $m_i$, state distribution $\rho_i$, dual variable $\Phi_i$, and terminal distribution $\rho_{T_i}$ for all populations

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**while** $k \leqslant K$ **do**  
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                    Update $\rho_n$, $m_n$, $\phi_n$ and $\rho_n^T$ according to (43), (45), (46), and (49) respectively;  
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            **end for**  
        **end for**  
    **end for**  
**end while**  
**return** : Optimal value of $\rho_n^*(t, x)$ and $m_n^*(t, x)$, $\forall n \in \{1, 2, \cdots, N\}$.

# Work 2: MFG for Mobile Crowd Sensing

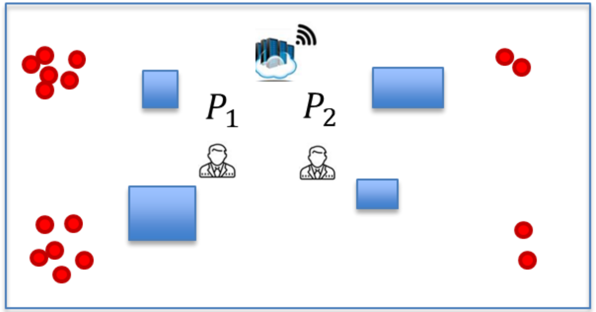
## Simulation

- Simulation Settings:

Two Operators in the middle

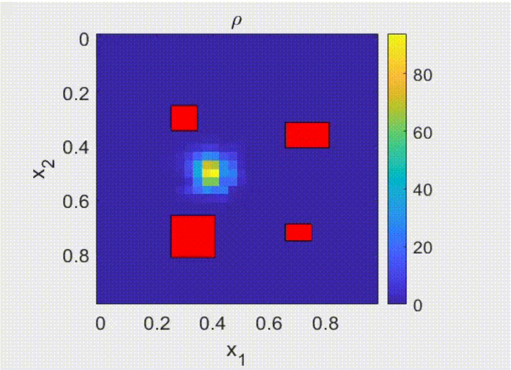
Four sensing sources
Area at corners

Four obstacles

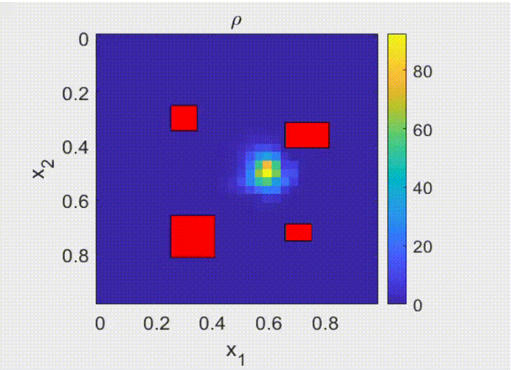



- Evolution of Distribution of vehicles:

Operator $P_1$'s vehicles:




Operator $P_2$'s vehicles:



# Work 2: MFG for Mobile Crowd Sensing

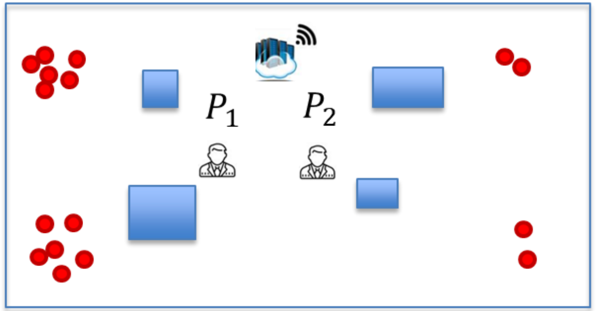
## Simulation: The competition behavior between operators

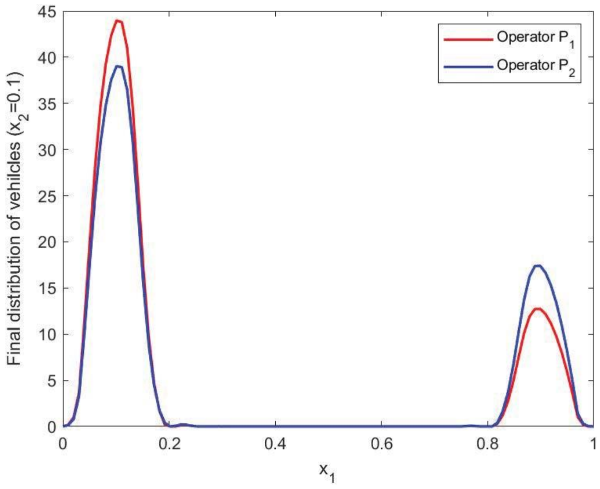
- Simulation Settings:

Two Operators in the middle

Four sensing sources Area at corners

Four obstacles

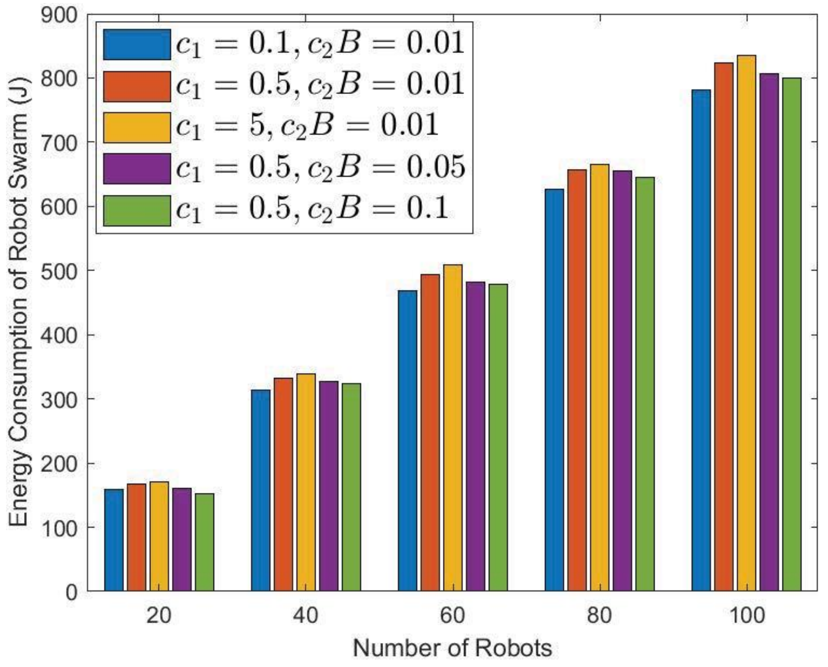



- Both $P_1$ and $P_2$ are higher in left that in the right. (More targets in the left)
- $P_1$ is higher than $P_2$ in the left area, and is lower in the right area.($P_1$ is closer to the left area.)
- In the right area, it is the opposite.

# Work 2: MFG for Mobile Crowd Sensing

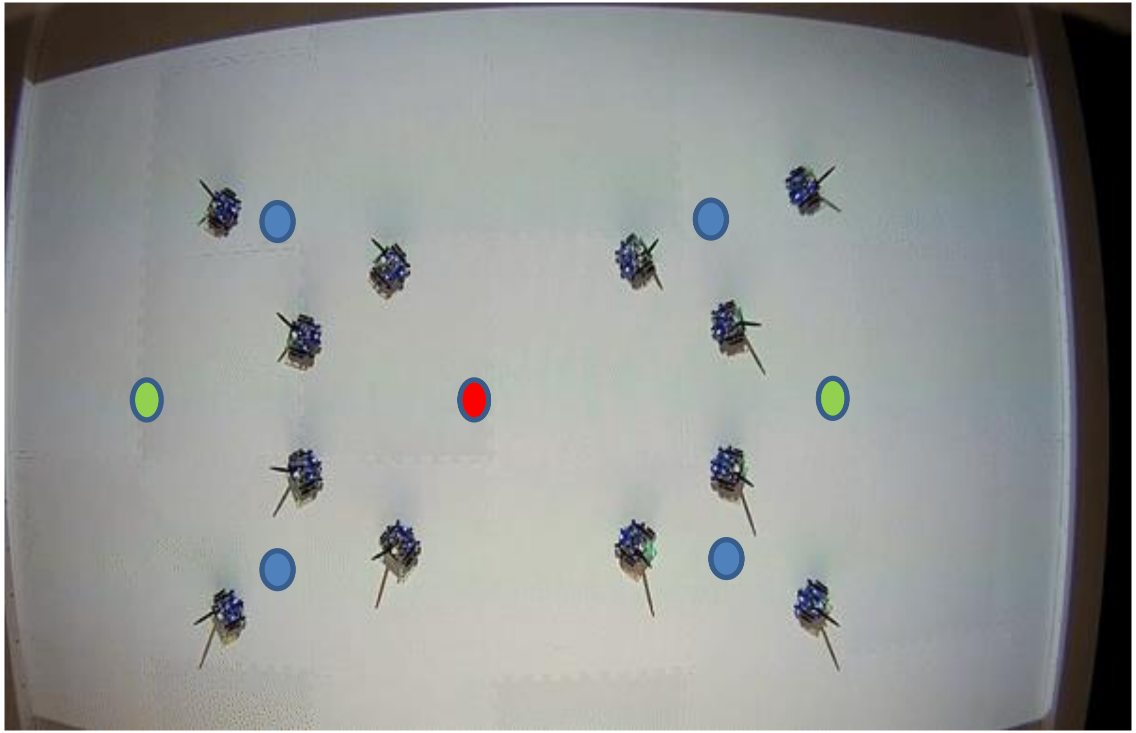
## Simulation: Sensitivity Analysis




- The energy consumption of vehicles increases approximately linearly.
- If the channel condition is bad, then vehicle will consume more energy.
- If the reward coefficient $c_1$ from the MCS is higher, then vehicle will consume more energy.

# Work 2: MFG for Mobile Crowd Sensing

- Robot Experiment: Evolution of Distribution



- There are three processes.
  Red: First target
  Blue: Second targets
  Green: Third targets
- Robots reached the targets in each process in an energy efficient way
- Implementability of MFG in robot systems

This experiment is finished at Robotarium by Georgia Tech.

# Outline

- Introduction
- Work 1: Time Efficient Offloading Optimization in Automotive Multi-Access Edge Computing Networks Using Mean-Field Games
- Work 2: Task Selection and Route Planning for Mobile Crowd Sensing Using Multi-Population Mean-Field Games
- **Work 3: MFG Augment: Data augmentation using Mean-field Games**
- Work 4: Joint Server Selection and Handover Design for Satellite-Based Federated Learning Using Mean-field Evolutionary Approach
- Conclusion & Future Work

# Work 3: MFG for Data Augmentation

- Motivation: Why Data Augmentation?

Data Augmentation are techniques used in machine learning models to increase the amount of data.

- Slightly modified the existing data.
- Create new data from existing data.

E.g.

Image Augmentation

- Advantages of Data Augmentation:

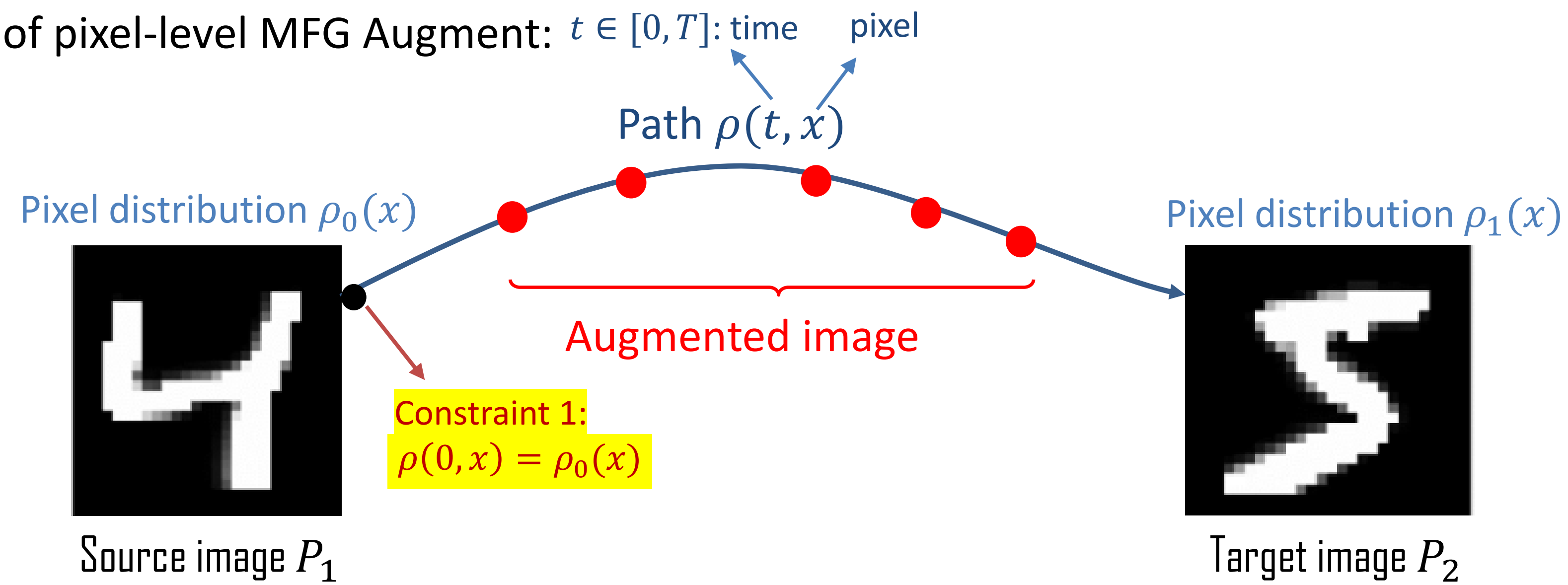
More data = Higher accuracy

Reduce overfitting = Higher accuracy

# Work 3: MFG for Data Augmentation

- Data Augmentation Using Mean-field Games: Pixel-level and Feature-level Augmentation

  - Idea of pixel-level MFG Augment:




Question: How to transform $\rho_0(x)$ into $\rho_1(x)$?

$u(t)$: Control of pixel value ("$u$" is the change of pixel value, i.e., $\frac{dx}{dt} = u$) → Constraint 2

# Work 3: MFG for Data Augmentation

- Pixel-level MFG Augment:

  $P_1, P_2$: Two images
  $x(t)$: Pixel values of the augmented picture at time "$t$" (32*32 for $P_i$ in Minist)
  $t \in [0, T]$: Time
  $u(t)$: Control of pixel value ("$u$" is the change of pixel value, i.e., $\frac{dx}{dt} = u$)
  $\rho_0, \rho_1$: Distribution of pixel values for the two pictures
  $\rho(t, x)$: Distribution of pixel values of the augmented picture at time "$t$"

- Pixel-level MFG data augmentation problem:

$$\min_{u,\rho} \boxed{\int_0^T \int_\Omega \frac{1}{2} \rho(t,x) \|u(t,x)\|_2^2 \, dx dt} + \boxed{\int_\Omega D_{KL}\left(\rho(T,x) \,\|\, \rho_1\right) dx}$$

$$s.t. \begin{cases} \frac{dx(t)}{dt} = u(t), \\ \rho(0,x) = \rho_0. \end{cases}$$

$\frac{dx(t)}{dt} = u(t)$ → Dynamics of pixel value $x$.

$\rho(0,x) = \rho_0$ → The initial augmented picture is $P_1$.

Physical meaning:
Minimize the distance between augmented pictures in adjacent times, so that the path is smooth, and the augmented images are more meaningful.

Physical meaning:
Minimize the KL divergence between the final augmented picture in the path and the target picture $P_2$.

# Work 3: MFG for Data Augmentation

- MFG Augment in Image-level Augmentation using G-prox PDHG Algorithm

  - Step 1: Define the Lagrangian function $L$ by introducing a dual variable $\Phi$.
  - Step 2：Solve the saddle-point Lagrangian problem.
  - Step 3: Sampling augmented images in the optimized “path”.

**Algorithm 1** MFG Augment in Image-level Augmentation

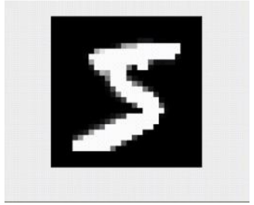
**Input:** Randomly choose two images with paired labels $(x_1, y_1)$, $(x_2, y_2)$; Two possibility parameters $\alpha, \beta \in [0,1]$; Two random generated variables $a, b \in [0,1]$ .
**if** $a \leq \alpha$ and $b \leq \beta$ **then**
  **Initialize:** The initial image's pixel distribution $\rho_{Initial}$ by normalizing $x_1$, and target's image pixel distribution $\rho_{Target}$ by normalizing $x_2$; Max iterations for G-prox PDHG algorithm $K$; Step size $\tau$, $\sigma$; Terminal Time $T$.
  **Define:** the Lagrangian function
  **while** $k \leqslant K$ **do**
    update $\rho$, $m$, $\phi$
    $k = k + 1$.
  **end while**
**end if**
**Output:** The augmented images $\rho(t_i, x)$ are obtained by sampling the optimal image augmentation path $\rho^*(t, x)$ at time instances $t = t_1, t_2, \ldots, t_N$, where the label of the augmented image $\rho(t_i, x)$ is $y_1$ if $t_i \leq 0.5T$, and its' label is $y_2$ if $t_i \geq 0.5T$.

# Work 3: MFG for Data Augmentation

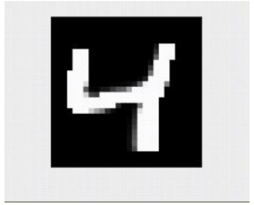
- Some visualization results for image-level MFG Augment:

  - Mnist:

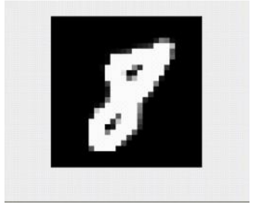
5-0



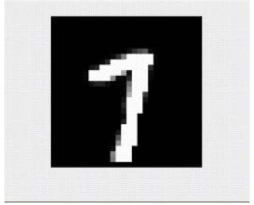
4-1



8-6



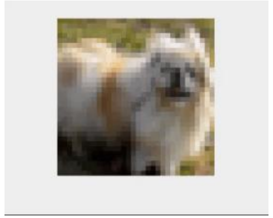
7-9



→ Label-variant transformation

  - CIFAR:

Dog



Horse

Vehicle

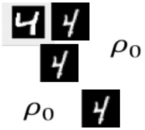
Bird

→ Label-invariant transformation

# Work 3: MFG for Data Augmentation

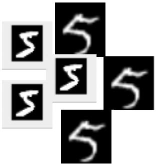
- Idea for MFG Augment: Feature-level Augmentation

  Compress the images into feature vectors, and using MFG to transform one feature distribution to another feature distribution.




Compress

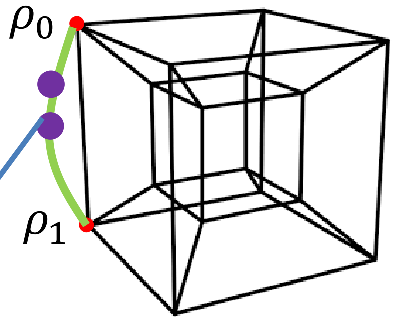
Distribution of source set of features $\rho_0$



Compress

Distribution of target set of features $\rho_1$

Latent space




Distribution of augmented feature vector

# Work 3: MFG for Data Augmentation

- Feature Level Augmentation MFG Problem: An Optimal Transport Problem

$$\min_{u,\rho} \int_0^T \int_\Omega \frac{1}{2} \rho(\underbrace{t}_{\text{time}}, \underbrace{x}_{\text{feature}}) \| u(t,x) \|_2^2 \, dx dt$$

$$s.t. \begin{cases} \dfrac{dx(t)}{dt} = u(t), & \longrightarrow \text{State dynamics} \\ \rho(0,x) = \rho_0. & \longrightarrow \text{Initial feature distribution} \\ \rho(T,x) = \rho_{Target_{Feature}set}. & \longrightarrow \text{Target feature distribution} \end{cases}$$

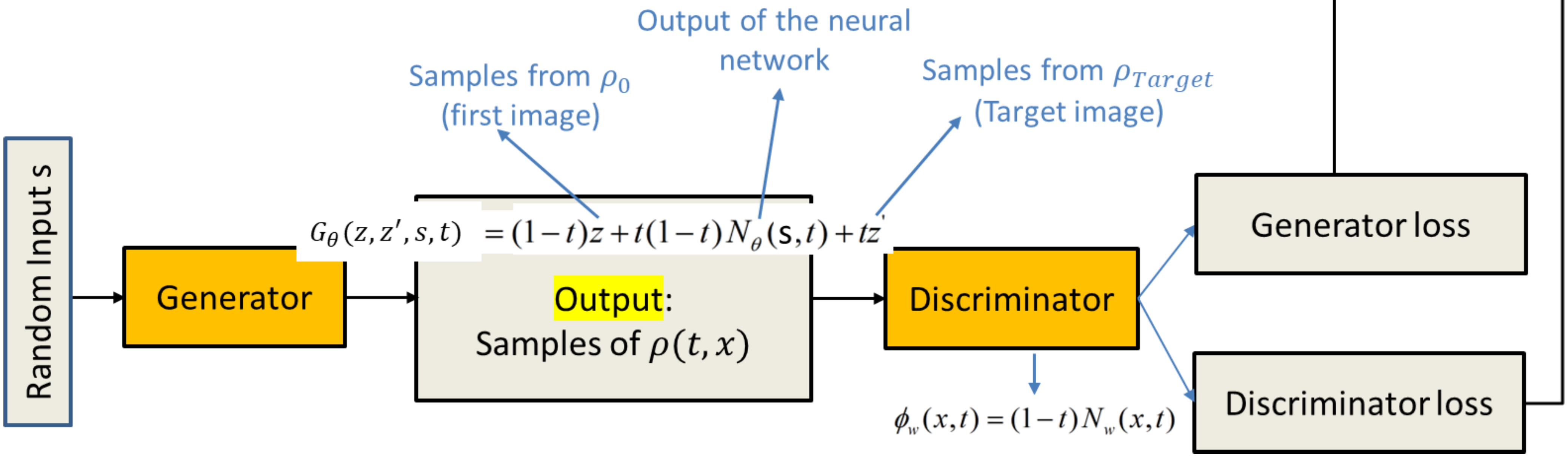
- Remark:

  $x$ is the learned feature with high dimension (100-1000 dimensional.)
  It is extremely complex to solve a high dimensional MFG problem using grid-based methods!

# Work 3: MFG for Data Augmentation

- Generative Adversarial Network (GAN) MFG solver:

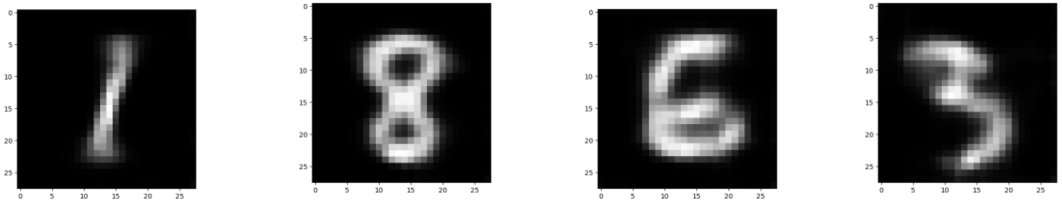
Lagrange problem: $\rho^*(t,x) = \arg \inf_{\rho(t,x)} \sup_{\phi(t,x)} \left\{ \int_0^T \int_\Omega \frac{1}{2}\rho(t,x)\|u(t,x)\|_2^2 - \phi(t,x)\left(\partial_t \rho(t,x) + \rho(t,x)u(t,x)\right) dx\,dt \right\}$



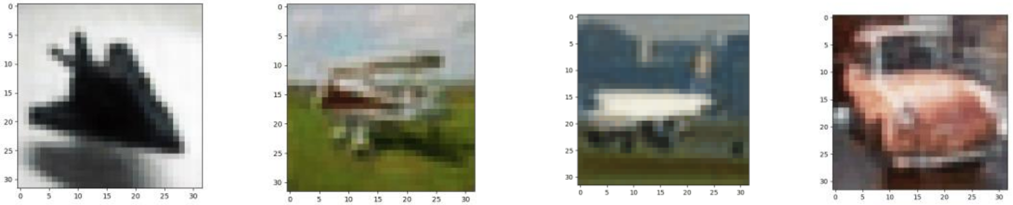
# Work 3: MFG for Data Augmentation

- Some visualization results for feature-level MFG Augment: Decoded Features

  - Mnist:



  - CIFAR10:



# Work 3: MFG for Data Augmentation

- Experiment Results: Mnist

| Reduced trainset size | Baseline | Cutout | Cutmix | Augmix | MFG Augment |
|---|---|---|---|---|---|
| 50 | 11.35 | 59.41 | 57.18 | 67.01 | **70.61** |
| 100 | 31.23 | 65.95 | 68.53 | 77.68 | **80.26** |
| 200 | 64.83 | 73.67 | 78.35 | 86.8 | **88.94** |
| 400 | 75.33 | 87.13 | 84.59 | 92.34 | **94.95** |
| 600 | 82.80 | 90.92 | 90.61 | 93.9 | **96.34** |
| 800 | 91.40 | 93.16 | 92.02 | 95.95 | **97.96** |
| 2,000 | 94.32 | 96.03 | 96.18 | 97.35 | **98.52** |

Table 1. Test accuracy (%) on reduced MNIST with trainset sizes varying from 50 - 2,000, trained with EfficientNet.

# Work 3: MFG for Data Augmentation

- Experiment Results: Cifar-10

| Reduced trainset size | Baseline | Cutout | Cutmix | Augmix | MFG Augment |
|---|---|---|---|---|---|
| 100 | 17.26 | 18.10 | 20.25 | 21.20 | **29.21** |
| 400 | 26.78 | 30.52 | 30.55 | 32.93 | **52.51** |
| 800 | 31.33 | 31.43 | 33.97 | 37.50 | **61.14** |
| 2,000 | 41.16 | 41.01 | 43.60 | 48.55 | **65.11** |
| 10,000 | 69.89 | 71.44 | 69.49 | 74.99 | **83.23** |
| 20,000 | 79.5 | 79.23 | 79.76 | 82.77 | **86.87** |
| 30,000 | 83.33 | 83.73 | 84.42 | 85.95 | **88.50** |
| 40,000 | 85.09 | 85.15 | 87.17 | 87.93 | **89.95** |
| 50,000 | 86.46 | 88.13 | 88.94 | 88.95 | **90.43** |

Table 3. Test accuracy on CIFAR-10 using several reduced trainset with datasize vary form 100 - 50,000, trained with EfficientNet.

# Work 3: MFG for Data Augmentation

- Experiment Results: Cifar-10

| Model | EfficientNet | ResNet-18 | ResNet-50 |
|---|---|---|---|
| Cutout | 88.13% | 88.27% | 89.61% |
| Cutmix | 88.94% | 91.37% | 92.49% |
| Augmix | 88.95% | 91.34% | 91.95% |
| MFG Augment | **90.43%** | **94.76%** | **94.69%** |

Table 4. Test accuracy (%) on CIFAR-10

- Experiment Results: ImageNet

| Reduced trainset size | Baseline | Cutout | Cutmix | Augmix | MFG Augment |
|---|---|---|---|---|---|
| 1/4 ImageNet | 54.18 | 55.07 | 57.57 | 57.03 | **61.13** |
| 1/2 ImageNet | 60.92 | 61.39 | 61.97 | 62.77 | **65.22** |
| 3/4 ImageNet | 65.75 | 67.04 | 69.65 | 68.91 | **69.73** |
| Full ImageNet | 69.76 | 70.25 | 71.52 | 71.49 | **72.26** |

TABLE V
TOP-1 ACCURACY (%) ON SEVERAL REDUCED IMAGENET, TRAINED WITH RESNET-18.

# Work 3: MFG for Data Augmentation

- Experiment Result: Affinity and Diversity Metric

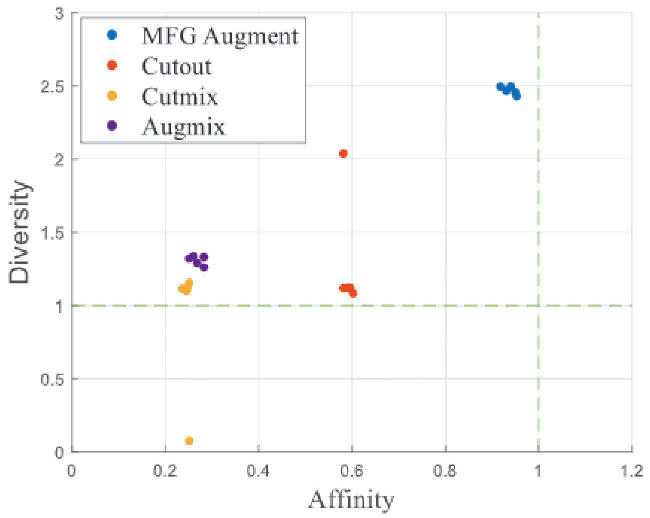



Figure 4. Affinity and diversity plane for Cutout, Cutmix, Augmix, and our MFG Augment on CIFAR-10, trained with EfficientNet.

- Remark:
  - Affinity quantifies how much an augmentation shifts the training data distribution from that learned by a model.
  - Diversity quantifies the complexity of the augmented data with respect to the model and learning procedure.
  - Data augmentation methods with high affinity and diversity usually has better performance.

# Outline

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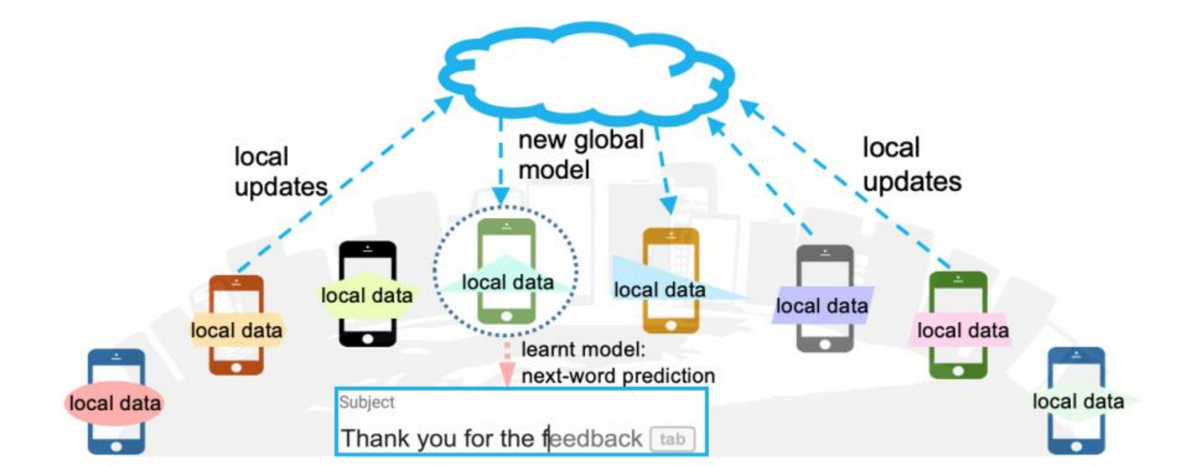
- **Work 4: Joint Server Selection and Handover Design for Satellite-Based Federated Learning Using Mean-field Evolutionary Approach**
- Conclusion & Future Work

# Work 4: MFG for Satellite-based Federated Learning

- Motivation: Federated Learning (FL):

  FL is a decentralized approach to machine learning where devices train models locally and share only updates with a central server, enhancing privacy and reducing data transmission.

- Advantages:
  - Data privacy and security
  - Reduced data centralization
  - Scalability
  - Model personation
  - Bandwidth Efficiency
  - …




**Text Prediction using FL[1]**

[1] "Federated Learning changes the ML data-sharing game", B. David, [Online] https://cornichegrowthadvisors.com/federated-learning-changes-the-data-sharing-game-in-ai/, Apr. 2017.

# Work 4: MFG for Satellite-based Federated Learning

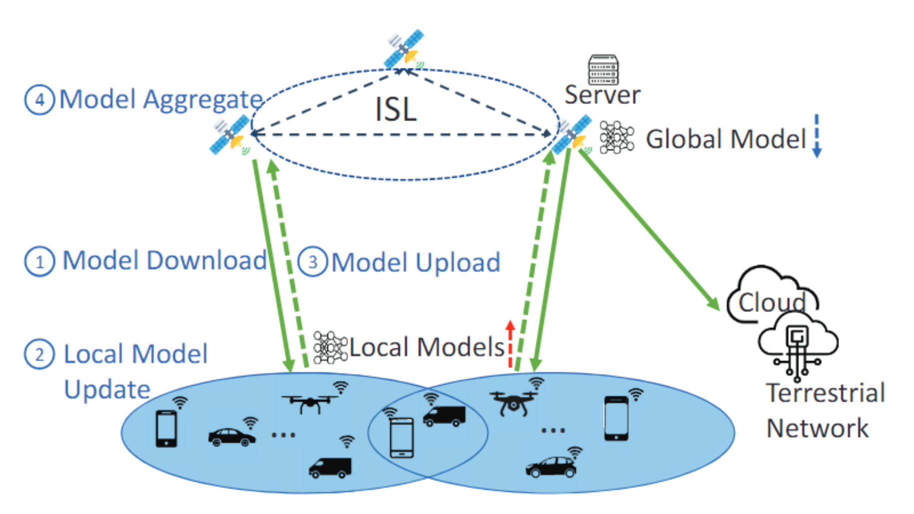
- Motivation: Satellite Communication Network
  - Advantages:
    - Global Coverage
    - Quick Deployment
    - Flexibility
    - Cost-efficiency for wide areas
    - High Broadband Capability

This work is supported by NSF ECCS 230-2469




# Work 4: MFG for Satellite-based Federated Learning

- System Model: SatComs-based FL network
  - Devices = Local Clients
  - Satellites = Servers
  - Applications: Traffic crowdsensing
    Location-based recommendation
    Pollution monitoring




- Challenges:
  - We focus on designing an incentive mechanism:
    - Scalability issue of devices
    - Devices' limited battery
    - High mobility of satellites, which to select?
    - Handover design when satellites moves out of devices reachable area?

- Step 1: Local model update
- Step 2: Model upload to satellites
- Step 3: Model aggregate at the satellite
- Step 4: Model download to devices

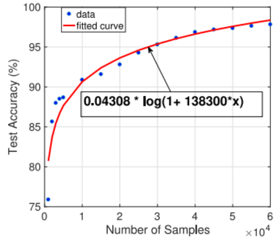
# Work 4: MFG for Satellite-based Federated Learning

- Problem Formulation: A joint server-selection and handover design optimization problem
  - The $m$-th device owns $D_m$ data quantity. $M, N$ is the number of devices and satellites respectively.
  - The $m$-th device decides the probability to select the $n$-th satellite and the satellite decide the handover action.

  The m-th devices action profile : $P_m^t = \{p_{m,1}^t, p_{m,2}^t, \cdots, p_{m,N}^t\}$, satellites action profile: $H_n^t = \{h_{n,1}^t, h_{n,2}^t, \ldots, h_{n,N'}^t\}$

- Cost for device $m$ to select satellite $n$ in the $k$-th round:

Example of $f$:




- Communication Cost of device $m$:

$$C_{m,n,k}^{cm} = \lambda_{m,n,k}^{cm} \underbrace{p_{m,n}^k}_{\text{Probability to choose satellite } n} \frac{\overbrace{S^{\beta_{m,n}^k}}^{\text{Model size}}}{\underbrace{g_{m,n}^k}_{\text{Channel Gain between device } m \text{ and satellite } n}},$$

Model size

Probability to choose satellite $n$

Channel Gain between device $m$ and satellite $n$

- Payoff from the satellite $n$

$$C_{m,n,k}^{pf} = \lambda_{m,n,k}^{pf} \left( \boxed{f}\left( \sum_{m=1}^{M} \boxed{\alpha_m} D_m p_{m,n}^k \right) \right) \boxed{\frac{\alpha_m D_m p_{m,n}^k}{\sum_{m=1}^{M} \alpha_m D_m p_{m,n}^k}} + b_{m,n}^k,$$

Data quantity that model owner k has

The profit is shared by all devices

A compensate term

# Work 4: MFG for Satellite-based Federated Learning

- Problem Formulation: A joint server-selection and handover design optimization problem
  - The $m$-th device owns $D_m$ data quantity.
  - The $m$-th device decides the probability to select the $n$-th satellite and the satellite decide the handover action.

  The m-th devices action profile : $P_m^t = \{p_{m,1}^t, p_{m,2}^t, \dots, p_{m,N}^t\}$, satellites action profile: $H_n^t = \{h_{n,1}^t, h_{n,2}^t, \dots, h_{n,N'}^t\}$

- Cost for device $m$ to select satellite $n$ in the $k$-th round :
  - Handover Cost of device $m$ choosing satellite $n$:

$$C_{m,n,k}^{hd} = \lambda_{m,n,k}^{hd} \boxed{\delta_{m,n}^k} p_{m,n}^k E_n H_{n,n'}^k \frac{\bar{S}_{m,n}^k}{c_{n,n'}^k},$$

The size of handover data

The constant transmission power of S2S communication.

Capacity of intersatellite link of $n$ with next round satellites $n'$

where $\delta_{m,n}^k$ is a given indicator variable

$$\delta_{m,n}^k = \begin{cases} 1, & \text{if satellite } n \text{ needs handover for device } m \\ 0, & \text{other wise.} \end{cases}$$

# Work 4: MFG for Satellite-based Federated Learning

- Problem Formulation: A joint server-selection and handover design optimization problem

$$\mathcal{P}_1 : \min_{\mathcal{P},\mathcal{H}} C_{m,n}$$

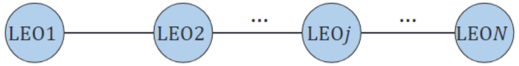
$$= \sum_{k=1}^{K} -C^{pf}_{m,n,k} + C^{cm}_{m,n,k} + C^{hd}_{m,n,k}$$

$$= \sum_{k=1}^{K} \underbrace{\boxed{-\lambda^{pf}_{m,n,k} \left( f\Big(\sum_{m=1}^{M} \alpha_m D_m p^k_{m,n}\Big) + b^k_{m,n} \right) \cdot \frac{\alpha_m D_m p^k_{m,n}}{\sum_{m=1}^{M} \alpha_m D_m p^k_{m,n}}}}_{\text{Payoff}} + \underbrace{\boxed{\lambda^{cm}_{m,n} p^k_{m,n} \frac{S^{\beta^k_{m,n}}}{g^k_{m,n}}}}_{\text{Communication cost}} + \underbrace{\boxed{\lambda^{hd}_{m,n,k} \delta^k_{m,n} p^k_{m,n} E_n H^k_{n,n'} \frac{\bar{S}^k_{m,n}}{c^k_{n,n'}}}}_{\text{Handover Cost}}$$

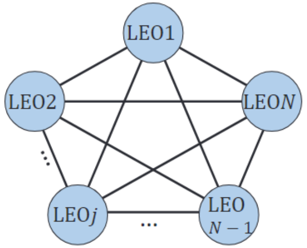
$$s.t. \begin{cases} \mathcal{C}_1 : p^k_{m,n} \geq 0, & \longrightarrow \text{Probability strategy} \\ \mathcal{C}_2 : \sum_{n=1}^{N} p^k_{m,n} = 1, \forall m \in \mathcal{M},\ \forall k \in \{1,2,\ldots,K\}, & \longrightarrow \text{Probability strategy} \\ \mathcal{C}_3 : \mathcal{B}_n(k) = \mathcal{B}^k_n, & \longrightarrow \text{Available satellite set at } k\text{-th communication round} \end{cases}$$

## Algorithm: A Mean-field Evolutionary Approach

### Step 1: Strategy graph construction




(a) 1-dimensional (1-d) strategy graph.




(b) Fully connected strategy graph.

### Step 2: Fokker-Planck dynamics as the gradient flow

$$\frac{\mathrm{d}P_n}{\mathrm{d}t} = \sum_{n' \in T(n)} \frac{1}{d_{n'}} P_{n'} [F_{m,n}(P) - F_{m,n'}(P) + \tau(\log P_{n'} - \log P_n)]^+$$

$$- \sum_{n' \in T(n)} \frac{1}{d_n} P_n [F_{m,n'}(P) - F_{m,n}(P) + \tau(\log P_n - \log PD_{n'})]^+$$

Agent strategy

Cost function

*where* $d_n$ *is the degree of node* $n$, $[\cdot]^+ = \max\{\cdot, 0\}$.

**Algorithm 1** Mean-field evolutionary approach for population game in Eq. (12)

1: Random initialize all devices' strategy profile $\mathcal{P}$
2: **while** (32) is not satisfied **do**
3:     **for** each device $m$ **do**
4:         gradient matrix $\Lambda_i$ construction by (29) and (30)
5:         update device $m$'s strategy $P_m^k$ by (31)
6:     **end for**
7: **end while**
8: Return: strategy profile $\mathcal{P}$

# Work 4: MFG for Satellite-based Federated Learning

## Simulation Results:

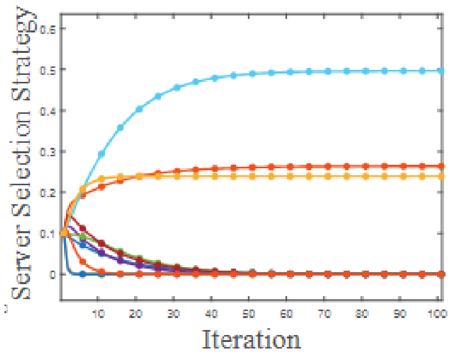
- Simulation setup:

  1000 mobile devices

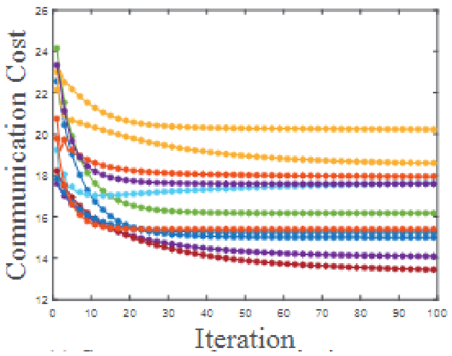
  10 available satellites in every communication round

| Parameters | Values |
|---|---|
| Total Number of Mobile Devices $M$ | $1,000$ |
| Devices' FL-attending probability | 0.1 |
| Number of available satellites $N$ in every communication round | $10 \sim 20$ |
| Devices' FL-attending probability | 0.1 |
| Devices' data size $D_m$ | $100 \sim 500M$ |
| Devices' data contribution index $\alpha_m$ | $1.0 \sim 5.0$ |
| Satellites' compensation bonus for devices $b^k_{m,n}$ | $1 \sim 2$ \$ |
| Satellites' transmission power in the ISL $E_n$ | $50 \sim 150$W |
| Satellites' handover indicator variable $\delta^k_{m,n}$ | $\mathcal{B}(0.1)$ |
| Channel gain between satellite $n$ and device $m$, i.e., $g_{m,n}$ | $-170 \sim -180db$ |
| Transmission capacity in the ISL $c^k_{n,n'}$ | $10 \sim 60$ Mbps |
| Devices' payoff coefficient $\lambda^{pf}_{m,n}$ | $3 \times 10^{-25} \sim 4 \times 10^{-25}$ |
| Devices' communication cost coefficient $\lambda^{cm}_{m,n}$ | $0.2 \sim 0.3$ |
| Satellites' handover cost coefficient $\lambda^{hd}_{m,n}$ | $5 \sim 5.5$ |
| MFEv time step $dt$ | $10^{-3}$ |
| MFEv stopping threshold $\eta_0$ | $10^{-4}$ |

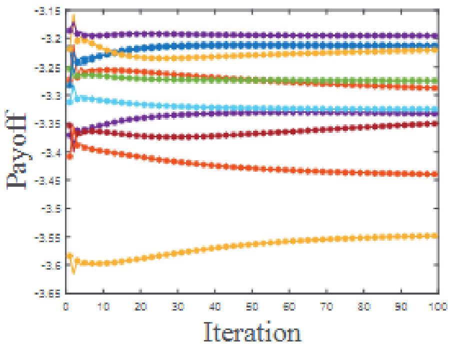
- Algorithm Convergence Analysis:



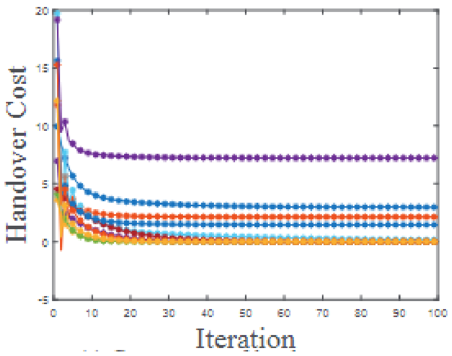
Strategy



Communication cost



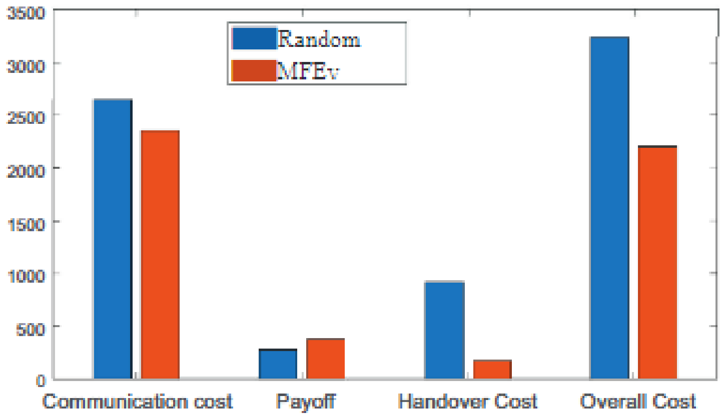
Payoff



Handover Cost

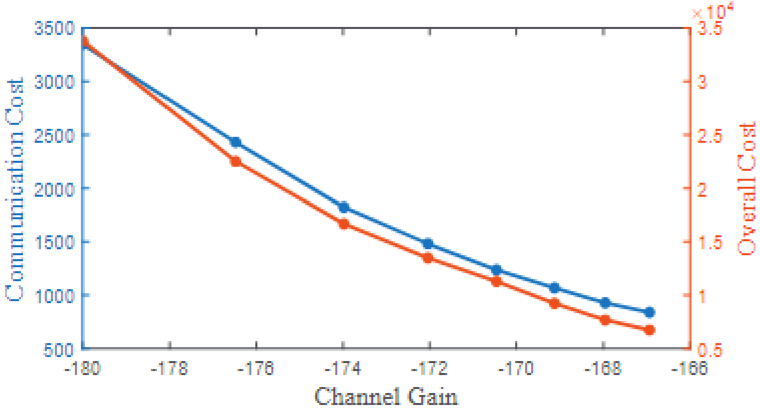
# Work 4: MFG for Satellite-based Federated Learning

- Simulation Results:
  - Random Strategy VS Proposed MFEv




  - Communication cost reduces 10.5%
  - Payoff increases 6%
  - Handover cost reduces 82%

  - Channel gain sensitivity analysis

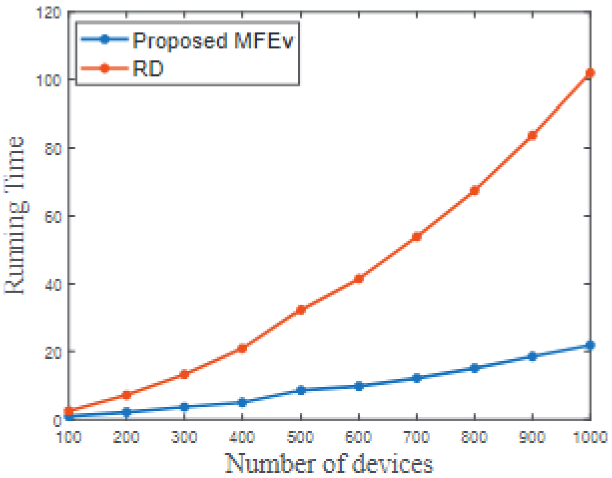



  - Channel gain is an important factor on cost
  - Communication cost and overall cost increases as the channel gain reduces

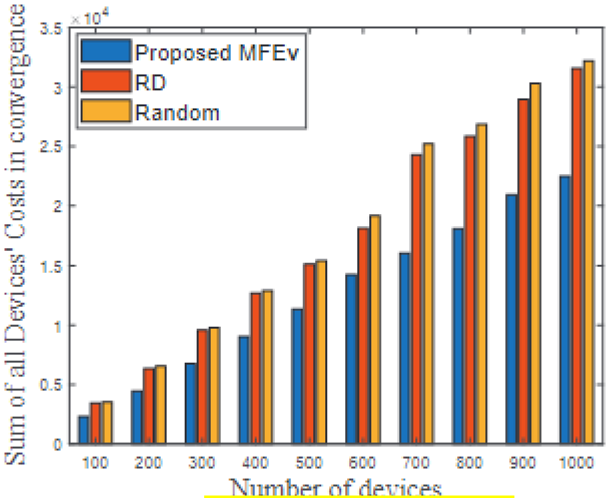
# Work 4: MFG for Satellite-based Federated Learning

## Simulation Results:

- Comparative experiment: Replicator Dynamics [2] (RD) VS Random Strategy VS Proposed MFEv




Code running time




Optimized costs

- The proposed MFEv reduce code running time about  80%
- The proposed MFEv reduce cost about 31% compared with RD [2], and 33% with Random Strategy.


[2] Y. Zou, S. Feng, D. Niyato, Y. Jiao, S. Gong, and W. Cheng, “Mobile device training strategies in federated learning: An evolutionary game approach,” in Int. Conf. Internet Things IEEE Green Comp. Commun. (GreenCom) and IEEE Cyber, Physical and Social Comp. and IEEE Smart Data, Atlanta, GA, Oct. 2019

# Conclusion & Future Work

## ☐ Conclusion

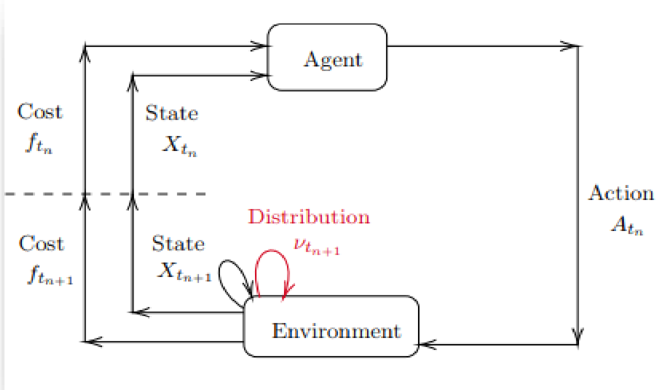
- Mean-field Game studies the strategic behavior of a large number of small interacting agents. By applicating the population behavior, MFG can reduce the computation complexity significantly.

- Work 1: MFG for Fast Offloading in Vehicular Edge Computing
  - ✓ MFG reduces the code running time significantly
  - ✓ Real-world implementation show the great efficiency
- Work 2: MFG for Task Selection and Path Planning in Mobile Crowd Sensing
  - ✓ MFG  reduces system complexity
  - ✓ Real-world robot experiment show the great effectiveness
- Work 3: MFG for Data Augmentation
  - ✓ MFG can summarize the whole pixel or feature information of images
  - ✓ MFG Augment achieves the highest test accuracy
- Work 4: MFG for Server Selection and Handover Design in SatComs-Based Federated Learning
  - ✓ Fokker-Planck equation is efficient to update agent's strategy
  - ✓ MFG reduce both the code running time and optimized cost compared with S.O.A methods

# Conclusion & Future Work

- Future Work
  - MFG and Graph-Embedding RL Routing Scheduling Optimization for SatComs-based Federated Learning
    - May connect MFG and GERL with Federated Learning in satellite communication network
    - May use MFG to simply the devices' and satellites' strategies
  - Learning MFG Equilibrium using Reinforcement Learning
    - May connect MFG with RL
    - May formulate a MFG-Markov Decision Process

Satellite Communication Networks




MFG-Markov Decision Process

# Publications

Book

- Yuhan Kang, Hao Gao, and Zhu Han, “Mean-Field Guided Machine Learning”, proposal accepted by Springer Science and Business Media.

Conference

- Y. Kang, S. Liu, W. Lee, H. Zhang, W. Li, and Z. Han, ``Joint task assignment and trajectory optimization for a mobile robot swarm by mean-field game," in Proc. IEEE Global Commun. Conf., Taipei, Taiwan, Dec. 2020.
- Y. Kang, S. Liu, H. Zhang, Z. Han, S. Osher, and H. V. Poor, ``Task selection and route planning for mobile crowd sensing using multi-population mean-field games," Proc. IEEE Int. Conf. Commun., Montreal, Canada, June. 2021.
- H. Zhang, Y. Kang, Z. Han, and H. Vincent Poor, ``AoI Minimization for Grant-Free Massive Access with Short Packets using Mean-Field Games," in Proc. IEEE Global Commun. Conf., Taipei, Taiwan, Dec. 2020.
- Y. Zhang, Y. Kang, C. Wu, J. Shi, D. Wang and Z. Han, "Carbon Emission-Aware Storage Control via Mean Field Game Coordination," 2022 IEEE 61st Conference on Decision and Control (CDC), Cancun, Mexico, Dec. 2022,
- D. Wang, W. Wang, Y. Kang and Z. Han, "Dynamic Data Offloading for Massive Users in Ultra-dense LEO Satellite Networks based on Stackelberg Mean Field Game," IEEE INFOCOM 2022 - IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), New York, NY, USA, May 2022.
- K. Chen, Y. Zhu, Y. Kang and Z. Han, "Few-Shot Correlation Estimation for Cross-Camera Video Analytics: A Mean-Field Game Approach," 2022 IEEE 33rd Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), Kyoto, Japan, Sept. 2022.

Journal

- Y. Kang, S. Liu, H. Zhang, W. Li, Z. Han, and S. Osher, "Joint Sensing Task Assignment and Collision-Free Trajectory Optimization for Mobile Vehicle Networks Using Mean-Field Games," in IEEE Internet of Things Journal, vol. 8, no. 10, pp. 8488-8503, May. 2021.
- Y. Kang, S. Liu, H. Zhang, Z. Han, S. Osher and H. V. Poor, "Task Selection and Collision-Free Route Planning for Mobile Crowdsensing Using Multi-Population Mean-Field Games," in IEEE Transactions on Green Communications and Networking, vol. 5, no. 4, pp. 1947-1960, Dec. 2021.
- Y. Kang, H. Wang, B. Kim, J. Xie, X. -P. Zhang and Z. Han, "Time Efficient Offloading Optimization in Automotive Multi-Access Edge Computing Networks Using Mean-Field Games," in IEEE Transactions on Vehicular Technology, vol. 72, no. 5, pp. 6460-6473, May. 2023.
- Y. Kang, Y. Zhu, D. Wang, Z. Han, and T. Basar, “Joint Server Selection and Handover Design for Satellite-Based Federated Learning Using Mean-field Evolutionary Approach”, in IEEE Transactions on Network Science and Engineering (Early Access).
- H. Zhang, Y. Kang, L. Song, Z. Han and H. V. Poor, "Age of Information Minimization for Grant-Free Non-Orthogonal Massive Access Using Mean-Field Games," in IEEE Transactions on Communications, vol. 69, no. 11, pp. 7806-7820, Nov. 2021.
- D. Wang, W. Wang, Y. Kang and Z. Han, "Distributed Data Offloading in Ultra-Dense LEO Satellite Networks: A Stackelberg Mean-Field Game Approach," in IEEE Journal of Selected Topics in Signal Processing, vol. 17, no. 1, pp. 112-127, Jan. 2023
- H. Gao, W. Lee, Y. Kang, W. Li, Z. Han, S. Osher, and H. V. Poor "Energy-Efficient Velocity Control for Massive Numbers of UAVs: A Mean Field Game Approach," in IEEE Transactions on Vehicular Technology, vol. 71, no. 6, pp. 6266-6278, Jun. 2022.


Should I approve Yuhan's Defense?
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# Thank you!

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