

Mean Field Games on Sparse and Dense Networks: The Graphexon MFG Equations

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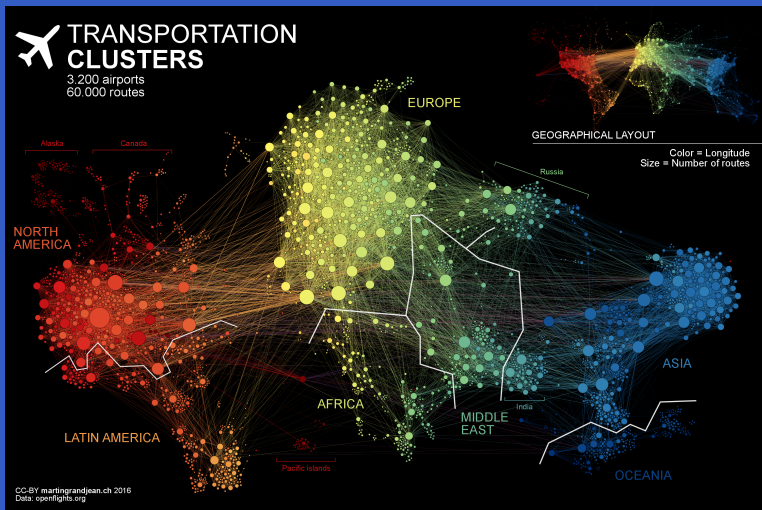
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Graphon Mean Field Games: Motivation

sp Non-uniform Network of Clusters



Finite Network Finite Population Mean Field Games

Consider a finite population distributed over a finite graph G_k with M_k clusters of agents at the M_k nodes.

This gives a total of $N = \sum_{l=1}^{M_k} |\mathcal{C}_l|$ agents.

For \mathcal{A}_i in the node cluster $\mathcal{C}(i)$, there are two dynamical input terms (scalar states for simplicity):

$$f_0(x_i, u_i, \mathcal{C}(i)) = \frac{1}{|\mathcal{C}(i)|} \sum_{j \in \mathcal{C}(i)} f_0(x_i, u_i, x_j) \quad (1)$$

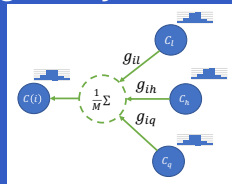
$$f_{G_k}(x_i, u_i, g_{\mathcal{C}(i)}^k) = \frac{1}{M_k} \sum_{l=1}^{M_k} g_{\mathcal{C}(i)\mathcal{C}_l}^k \left[\frac{1}{|\mathcal{C}_l|} \sum_{j \in \mathcal{C}_l} f(x_i, u_i, x_j) \right] \quad (2)$$

NB: f_{G_k} uses the sectional (i.e. vertex neighbourhood) information $g_{\mathcal{C}(i)\bullet}^k$.

Finite Network Finite Population MF Games: Agent Dynamics in Clusters at Nodes

The state process of \mathcal{A}_i in its cluster $\mathcal{C}(i)$ is given by the SDE

$$dx_i(t) = \frac{1}{|\mathcal{C}(i)|} \sum_{j \in \mathcal{C}(i)} f_0(x_i, u_i, x_j) dt + \frac{1}{M_k} \sum_{l=1}^{M_k} g_{\mathcal{C}(i)\mathcal{C}_l}^k \left[\frac{1}{|\mathcal{C}_l|} \sum_{j \in \mathcal{C}_l} f(x_i, u_i, x_j) \right] dt + \sigma dw_i \quad (3)$$



$$= f_0(x_i, u_i, \mathcal{C}(i)) dt + f_{G_k}(x_i, u_i, g_{\mathcal{C}(i)}^k) dt + \sigma dw_i \quad (4)$$

$$1 \leq i \leq N$$

Nash Equilibria

Fundamental Notion of Non-cooperative Game Equilibrium:

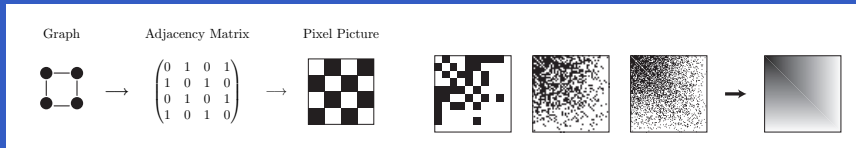
The controls $\mathcal{U}^0 = \{u_i^0; u_i^0 \text{ adapted to } \mathcal{U}_{loc,i}, 1 \leq i \leq N\}$, generate an ε -Nash Equilibrium w.r.t. $\{J_i; 1 \leq i \leq N\}$ if, for all i , a unilateral control law u_i utilizing the global information pattern \mathcal{U} satisfies

$$J_i(u_i^0, u_{-i}^0) - \varepsilon \leq \inf_{u_i \in \mathcal{U}} J_i(u_i, u_{-i}^0) \leq J_i(u_i^0, u_{-i}^0)$$

So, by definition, a unilateral move against a population of agents all of whom are utilizing a Nash strategy cannot yield a benefit of more than $\varepsilon > 0$ for the unilateral agent.

From Graphons to Graphexons

Graph Sequence Convergence to Graphons



Definition: A **graphon** (Lovasz, AMS 2012) is a bounded symmetric Lebesgue measurable function $\mathbf{W} : [0, 1]^2 \rightarrow [0, 1]$.

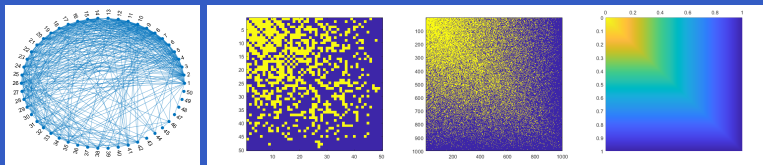
Graphons may be interpreted as weighted undirected edge graph limits on the vertex set $[0, 1]$.

Theorem [Lovasz and Szegedy, 2006; LL AMS2012]
Under the cut metric the graphon space $(\mathcal{W}_{[0,1]}, \delta_{\square})$ is compact.

Graphons

Graphon [Lov2012]: A measurable function $[0, 1]^2 \rightarrow [0, 1]$

Example: Unif. Attachment Graphon: $g(\alpha, \beta) = 1 - \max(\alpha, \beta)$



Convergence of “adjacency matrices” to graphons is in the cut metric. The space of graphons is compact.

We use stronger topology of $L_2[0, 1]$ operator convergence.

Infinite Network Infinite Population MF Games: Drifts of Each Agent in its Cluster

Assume :

- (i) **The graph sequence $G_k; 1 \leq k < \infty$ has a unique graphon limit function $g(\alpha, \beta), \alpha, \beta \in [0, 1]$.**
- (ii) **The subpopulation at each node tends to infinity, giving the local mean field μ_α and the global set of mean fields $\mu_G = \{\mu_\beta; 0 \leq \beta \leq 1\}$. Hence resulting in the drifts:**

$$f_0[x_\alpha, u_\alpha, \mu_\alpha] := \int_{\mathbb{R}^n} f_0(x_\alpha, u_\alpha, z) \mu_\alpha(dz), \quad (5)$$

$$f[x_\alpha, u_\alpha, \mu_G; g_\alpha] := \int_0^1 \int_{\mathbb{R}^n} f(x_\alpha, u_\alpha, z) g(\alpha, \beta) \mu_\beta(dz) d\beta, \quad (6)$$

yielding the local limit graphon drift dynamics (and similarly for costs $\tilde{l}[x, u, \mu_G; g_\alpha]$):

$$\tilde{f}[x_\alpha, u_\alpha, \mu_G; g_\alpha] := f_0[x_\alpha, u_\alpha, \mu_\alpha] + f[x_\alpha, u_\alpha, \mu_G; g_\alpha]$$

Graphon Mean Field Game (GMFG) Equations

HJB generates the value function V^α for the representative agent at node α at Nash equilibrium.

$$\begin{aligned} [\text{HJB}](\alpha) \quad - \frac{\partial V^\alpha(t, x)}{\partial t} &= \inf_{u \in U} \left\{ \tilde{f}[x, u, \mu_G; g_\alpha] \frac{\partial V^\alpha(t, x)}{\partial x} \right. \\ &\quad \left. + \tilde{l}[x, u, \mu_G; g_\alpha] \right\} + \frac{\sigma^2}{2} \frac{\partial^2 V^\alpha(t, x)}{\partial x^2}, \\ V^\alpha(T, x) &= 0, \quad (t, x) \in [0, T] \times \mathbb{R}, \quad \alpha \in [0, 1], \end{aligned} \quad (7)$$

FPK generates the mean field density for the representative agent at node α at Nash equilibrium.

$$\begin{aligned} [\text{FPK}](\alpha) \quad \frac{\partial p_\alpha(t, x)}{\partial t} &= - \frac{\partial \{ \tilde{f}[x, u^0, \mu_G; g_\alpha] p_\alpha(t, x) \}}{\partial x} \\ &\quad + \frac{\sigma^2}{2} \frac{\partial^2 p_\alpha(t, x)}{\partial x^2}, \quad p_\alpha(0) = p_0 \quad (8) \\ [\text{BR}](\alpha) \quad u^0 &= \varphi(t, x | \mu_G; g_\alpha). \end{aligned}$$

GMFG Eqns: Existence, Uniqueness, epsilon-Nash

Theorem: GMFG Existence and Uniqueness [PEC-Minyi Huang CDC2018, CDC 2019, SICON 2021]

For U compact, subject to regularity conditions **there exists a unique Nash equilibrium solution** $(V^\alpha, \mu_\alpha(\cdot))_{\alpha \in [0,1]}$ to the GMFG equations (7) and (8).

Moreover subject to a graph convergence condition, the **GMFG epsilon - Nash Property holds**.

The feedback control **best response (BR) strategy** $\varphi(t, x_\alpha | \mu_G(\cdot); g_\alpha)$ for each agent depends only upon **the agent's state and the graphon mean fields**: (x_α, μ_G) .

For networked LQG and control affine systems the GMFG equation solvability depends on the complexity of the graphon.

GMFG refs: CDC 2018-23, IEEE TAC 2020, 2021, 2023, MTNS 2022, ESAIM 2022, IFAC 2023, Automatica + SCL 2024

Inconvenient Truths Provoking "Graphexon Response"

Graphon theory is widely employed in large Network Mean Field Control and Games studies.

Fact: non-zero graphon limits exist only if "dense", i.e. the number of edges scales quadratically with node cardinality, equivalently, **have strictly positive asymptotic density**.

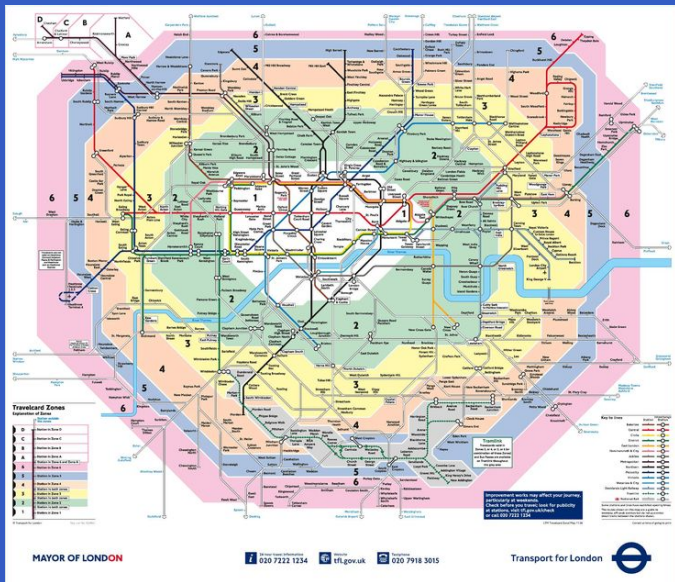
(Shall call non-dense network sequences sparse.)

Hence bounded node degree network sequences have **Zero Limit** graphons. True even with refined definitions of sparse.

But (i) **NO** large real world networks are dense - all are sparse due to low bounded node degree: Metros, Power grids, etc.

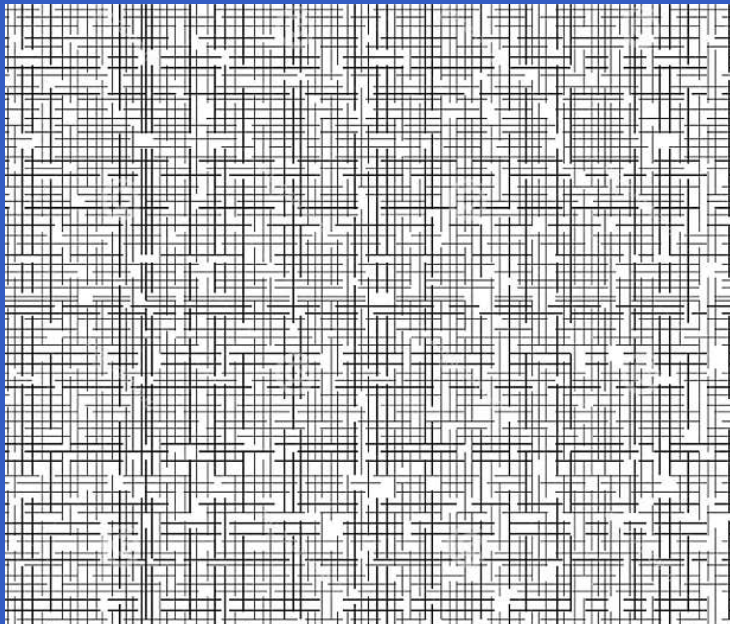
(ii) And there is **NO** metric based topology for graphs in R^m , $2 \leq m$, since nodes of a limit graphon G are combinatorically indexed by reals in $[0, 1]^m$.

London Underground Bounded Degree Real Network



Large Sparse Network : Node degree = 4, $n = 1, 2, ..$

Rectangular Lattice Vertices and Edges in the Unit Square: A Sparse Graph



Networks in Space: Vertexons and Graphexons

Vertexon and Graphexon Sequences

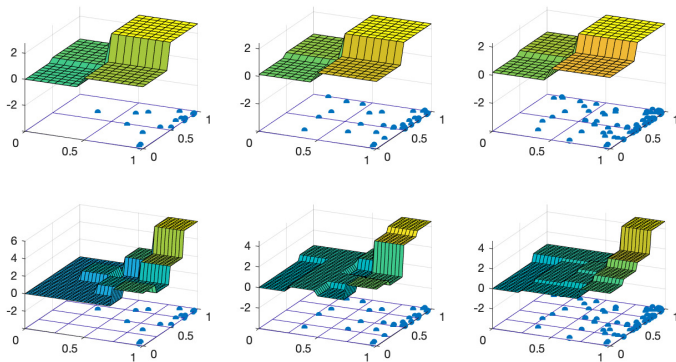
Let each of a sequence of **simple graphs** $\{G_n; n \in \mathbb{N}\}$ have its **vertices** embedded in $[0, 1]^m$, and each of the corresponding **edge vertex pairs** be embedded in R^{2m} .

Take **cubic partitions (voxels)** of $[0, 1]^m$ and $[0, 1]^{2m}$ of edge length $1/k$.

Definition: **Vertexon and Graphexon $\{n, k\}$ -sequences:**

k — indexed **step functions** on $[0, 1]^m$ (resp. $[0, 1]^{2m}$) with steps of **height proportional to the fraction** of vertices (resp. vertex pairs connected by edges) of G_n contained in the corresponding k —voxels.

Networks in Space: Embedded Graphs: Vertexon and Graphexon $\{n, k\}$ -Sequences



k indexes the partition level corresponding to a row above, while n indexes the total number of elts. per graph passing L to R.

Vertexon and Graphexon Limits

Vertexon (limits) are weak (double) limit measures on $[0, 1]^m$ of Vertexon $\{n, k\}$ sequences of embedded graph sequences.

Graphexon (limits) are weak (double) limit measures on $[0, 1]^{2m}$ of Graphexon $\{n, k\}$ sequences of embedded graph sequences.

Networks in Space: Embedded Graphs: Vertexons and Graphexons

Theorem: Embedded Vertexon-Graphon Stepping Function Limits (PEC CDC 2022)

Consider an $M = [0, 1]^m$ embedded graph sequence $\{G_n = (V_n, E_n), n \in \mathbb{N}\}$.

Then there exists a joint vertexon-graphon sub-sequence converging weakly in measure to a limit vertexon - graphon measure pair:

$$G_{n_v} = (U_{n_v}, E_{n_v})(z, w) \rightarrow (V_\infty, W_\infty)(dz, dw) \text{ a.e. } M \times M^2 \text{ as } n_v \rightarrow \infty$$

Networks in Space: Embedded Graphs: Vertexons and Graphexons

(a) **Graphexon limits have topologies**: the metrics on spaces of distributions.

(b) **All (non-empty) graph sequences have non-zero subsequential limits**.

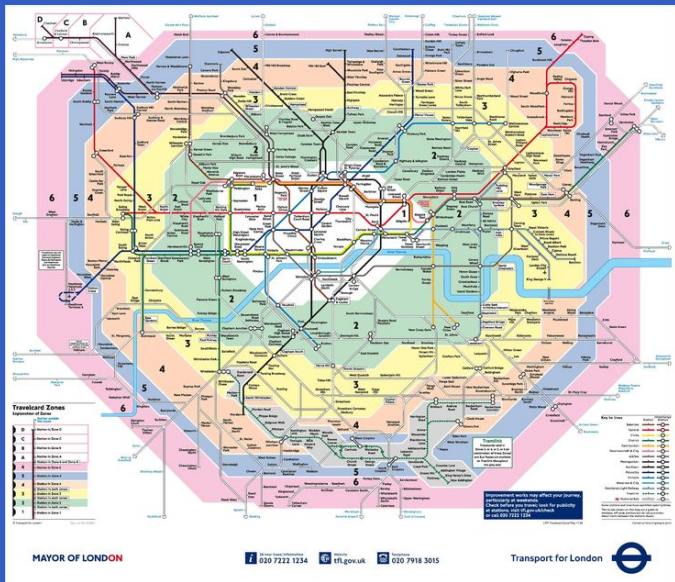
Overview:

Graphon (limits) **map $[0, 1]$ node indexed graph sequences to bounded measurable function (limits) on the unit square**.

Graphexon (limits) **map (m dim) embedded graph sequences to measure limits on the ($2m$ dim) unit cube**.

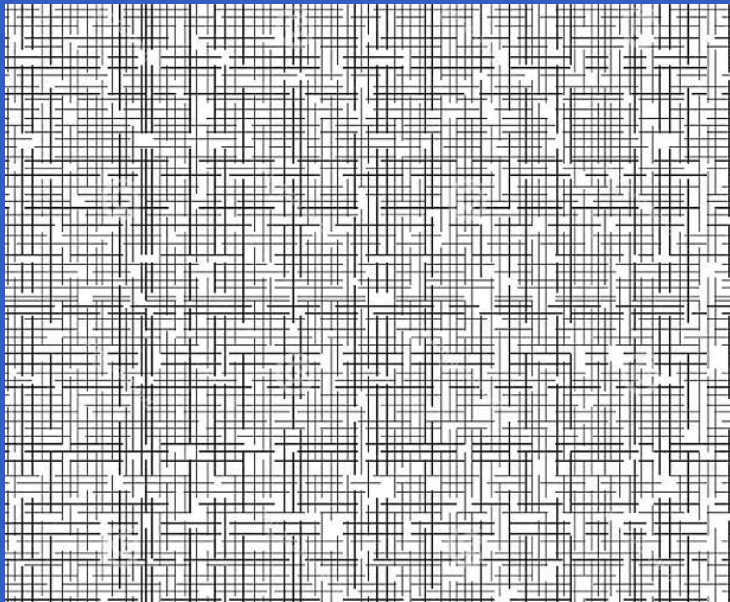
Normalizing any non-zero graphon $g(\alpha, \beta)$ on $[0, 1]^2$ yields an a.c. graphexon $\frac{g(\alpha, \beta)}{\iint (g(\alpha, \beta))}$ on $[0, 1]^2$.

Recall London Underground Network Example



Recall Large Sparse Network : Node degree = 4.

Rectangular Lattice Vertices and Edges in the Unit Square: A Sparse Graph



Infinite Network Infinite Population MF Games: Drifts of Each Agent in its Cluster

Assume :

- (i) **The graph sequence $G_k; 1 \leq k < \infty$ has a unique graphon limit function $g(\alpha, \beta), \alpha, \beta \in [0, 1]$.**
- (ii) **The subpopulation at each node tends to infinity, giving the local mean field μ_α and the global set of mean fields $\mu_G = \{\mu_\beta; 0 \leq \beta \leq 1\}$. Hence resulting in the drifts:**

$$f_0[x_\alpha, u_\alpha, \mu_\alpha] := \int_{\mathbb{R}^n} f_0(x_\alpha, u_\alpha, z) \mu_\alpha(dz), \quad (9)$$

$$f[x_\alpha, u_\alpha, \mu_G; g_\alpha] := \int_0^1 \int_{\mathbb{R}^n} f(x_\alpha, u_\alpha, z) g(\alpha, \beta) \mu_\beta(dz) d\beta, \quad (10)$$

yielding the local limit graphon drift dynamics (and similarly for costs $\tilde{l}[x, u, \mu_G; g_\alpha]$):

$$\tilde{f}[x_\alpha, u_\alpha, \mu_G; g_\alpha] := f_0[x_\alpha, u_\alpha, \mu_\alpha] + f[x_\alpha, u_\alpha, \mu_G; g_\alpha]$$

Graphexon Mean Field Game (GMFG) Equations

Example: (MH-PEC) **Vertexon-Graphexon of the Infinite 2-dimensional Rectangular Lattice** - in 4-dimensions!!

Consider the limit of a uniformly distributed uniformly rectangular (i.e. square) grid in $[0, 1]^2$.

Vertexon: A uniform unit density on $[0, 1]^2$ which is evidently **not singular**.

Graphexon: The sum of two **singular** measures supported on two foliations of $[0, 1]^4$, namely

$$\left\{ \frac{1}{2} \delta(p-x) \delta(q-y) + \frac{1}{2} \delta(p-y) \delta(q-x); 0 \leq x, y, p, q \leq 1 \right\}.$$

Infinite Network Infinite Population MF Games: Drifts of Each Agent in its Cluster: Graphexon Case

Assume :

- (i) **The graphexon sequence $G_k; 1 \leq k < \infty$ has a unique graphexon limit measure $N_\alpha(d\beta), \alpha, \beta \in [0, 1]$.**
- (ii) **The subpopulation at each node tends to infinity, giving the local mean field μ_α and the global set of mean fields $\mu_G = \{\mu_\beta; 0 \leq \beta \leq 1\}$. Hence resulting in the drifts:**

$$f_0[x_\alpha, u_\alpha, \mu_\alpha] := \int_{\mathbb{R}^n} f_0(x_\alpha, u_\alpha, z) \mu_\alpha(dz), \quad (11)$$

$$f[x_\alpha, u_\alpha, \mu_G; N_\alpha] := \int_0^1 \int_{\mathbb{R}^n} f(x_\alpha, u_\alpha, z) N_\alpha(d\beta) \mu_\beta(dz), \quad (12)$$

yielding the local limit graphon drift dynamics (and similarly for costs $\tilde{l}[x, u, \mu_G; g_\alpha]$):

$$\tilde{f}[x_\alpha, u_\alpha, \mu_G; g_\alpha] := f_0[x_\alpha, u_\alpha, \mu_\alpha] + f[x_\alpha, u_\alpha, \mu_G; N_\alpha]$$

Graphexon MFG Equations (MH-PEC CDC24 sub.)

On a Graphexon with singular measure N_α the GXMFG HJB generates a **value function V^α for the representative agent at node α at Nash equilibrium** with prescribed dynamics on the support of measure.

$$\begin{aligned} [\text{HJB}](\alpha) \quad - \frac{\partial V^\alpha(t, x)}{\partial t} &= \inf_{u \in U} \left\{ \tilde{f}[x, u, \mu_G; N_\alpha] \frac{\partial V^\alpha(t, x)}{\partial x} \right. \\ &\quad \left. + \tilde{l}[x, u, \mu_G; N_\alpha] \right\} + \frac{\sigma^2}{2} \frac{\partial^2 V^\alpha(t, x)}{\partial x^2}, \end{aligned}$$

FPK generates the mean field for the representative agent at α

$$\begin{aligned} [\text{FPK}](\alpha) \quad \frac{\partial p_\alpha(t, x)}{\partial t} &= - \frac{\partial \{ \tilde{f}[x, u^0, \mu_G; N_\alpha] p_\alpha(t, x) \}}{\partial x} \\ &\quad + \frac{\sigma^2}{2} \frac{\partial^2 p_\alpha(t, x)}{\partial x^2}, \quad p_\alpha(0) = p_0 \end{aligned}$$

$$[\text{BR}](\alpha) \quad u^0 = \varphi(t, x | \mu_G; N_\alpha).$$

Example: Heat Equation Influence Between NNs on a Ring Graphexon (MH-PEC CDC24 sub.)

Scalar nonlinear model with affine control drift dynamics at node α

$$\begin{aligned} f[x_\alpha, u_\alpha, \mu_G; N_\alpha] &:= \int_0^{2\pi} \int_{\mathbb{R}^n} f(x_\alpha, u_\alpha, z) N_\alpha(d\beta) \mu_\beta(dz) \\ &:= \int_0^{2\pi} \int_{\mathbb{R}^n} D\partial_\beta^2 m_\beta(t) \delta(\alpha - \beta) \mu_\beta(dz), \end{aligned}$$

Hence:

$$\begin{aligned} dx_\alpha(t) &= f_0(\alpha, x_\alpha(t), u_\alpha(t), \mu_\alpha(t))dt \\ &\quad + D\partial_\alpha^2 m_\alpha(t)dt + \sigma dw_\alpha(t), \end{aligned}$$

where $\alpha \in [0, 2\pi)$, $x_\alpha(t) \in \mathbb{R}$, $u_\alpha(t) \in \mathbb{R}$, $w_\alpha(t) \in \mathbb{R}$, and

$$m_\alpha(t) = \int_{\mathbb{R}} x \mu_\alpha(t, dx).$$

Example: Heat Equation Influence Between NNs on a Ring Graphexon (MH-PEC CDC24 sub.)

How does the coupling term $\partial_{\alpha}^2 m_{\alpha}$ arise?

- In this case we consider a ring graphexon corresponding to a ring in $[0, 1]^2$ with parameterised singular graphexon $\delta(\alpha - \beta)$ on $[0, 2\pi)^2$. Agent interactions are modelled as nearest neighbour influences.
- Each node's local mean field m_{α_i} receives an averaging effect with respect to two neighbouring nodes' $m_{\alpha_{i-1}}$ and $m_{\alpha_{i+1}}$.
- Suitable scaling leads to the second order term $\partial_{\alpha}^2 m_{\alpha}$, which also has a heat equation diffusion interpretation.

Example: Heat Equation Influence Between NNs on a Ring Graphexon (MH-PEC CDC24 sub.)

$$\begin{aligned} HJB \quad \partial_t V_\alpha(t, x) = & \partial_x V_\alpha(t, x) f_0(x, \mu) - \frac{1}{4} (\partial_x V_\alpha(t, x))^2 \\ & + D \partial_\alpha^2 m_\alpha(t) + L_0(x, \mu) + \frac{\sigma^2}{2} \partial_x^2 V_\alpha(t, x). \end{aligned}$$

$$\begin{aligned} FPK \quad \partial_t p_\alpha(t, x) = & - \partial_x \{ [f(x, \mu_\alpha(t)) - (1/2) \partial_x V_\alpha(t, x) \\ & + D \partial_\alpha^2 m_\alpha(t)] p_\alpha(t, x) \} \\ & + \frac{\sigma^2}{2} \partial_x^2 p_\alpha(t, x), \end{aligned}$$

where $p_\alpha(t, \cdot)$ is the probability density function of $\mu_\alpha(t)$.

In the linear dynamics quadratic costs case existence and uniqueness of solutions have been established (MH+PEC, CDC24 submitted) but ϵ -Nash remains to complete!

Networks in Space: Vertexons and Graphexons

Summary and Conclusions

- (1) Work with Alex Dunyak on **Q-noise driven Graphon/Graphexon LQG** control, games, filtering and its connections to Network Science and Low-rank graphon approximations (following Shuang Gao) has **not** been presented here.
- (2) Recall that ***all* spatially embedded sparse** and dense graphs have **graphexon (weak measure) limits**. To Explore!
- (3) In principle, the graphexon framework permits the **application of diff. calculus** in GXMFG/C systems. Explore!
- (4) In the absolutely continuous case the graphexon framework enables the analysis of maxima, minima, and saddle points of mean field game equilibrium values as functions of location. Hence can define **"Nash-optimal places"**. Explore!