On the Limit Performance of Floating Gossip

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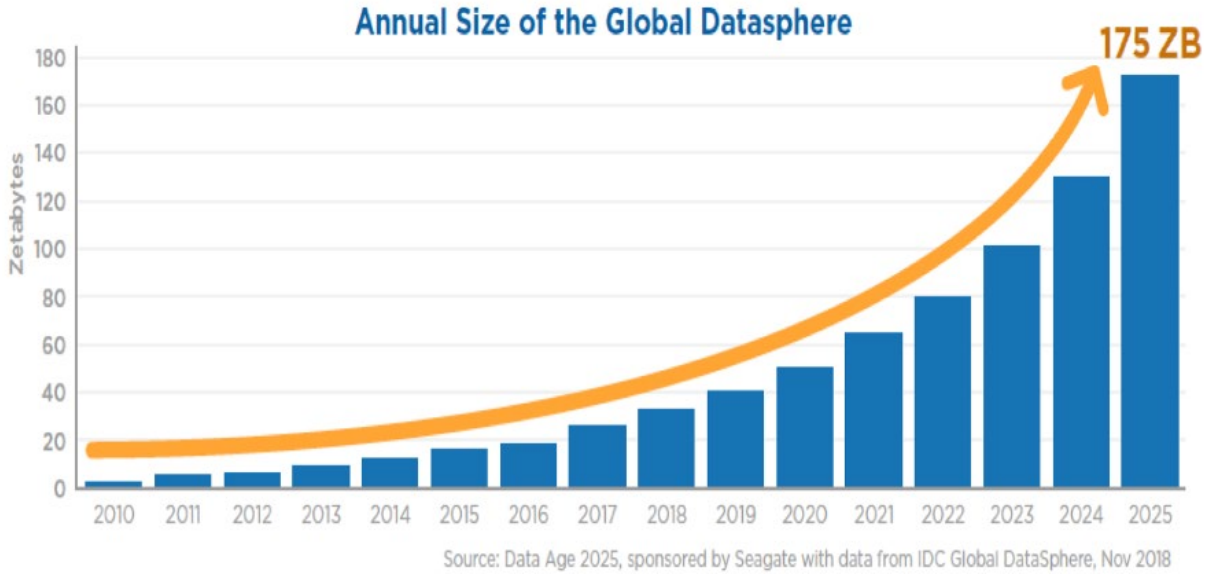
The push towards Edge Computing is fostering distributed learning schemes

- Data production is growing at a vertiginous pace



- Most of that data is produced at the edge of the network
- **Scalability: keep data storage and elaboration at the edge**

Distributed Learning

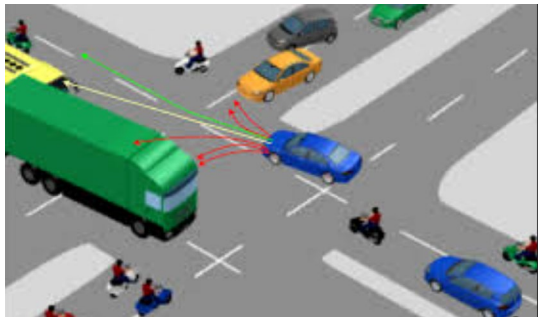
We focus on distributed continual learning

Learning is continual (in some way or another)

- Environment which keeps on changing
- Involves forgetting past, outdated info

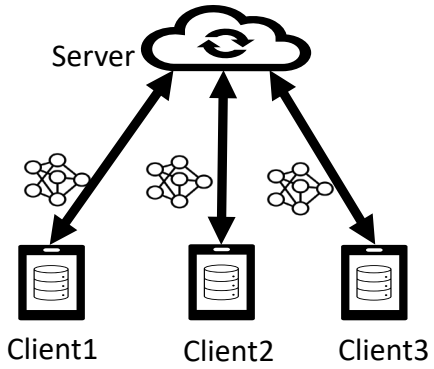
Example 1: Personalized, location-based recommendations, e.g. in amusement parks

Example 2: Vehicular trajectory prediction in urban scenarios



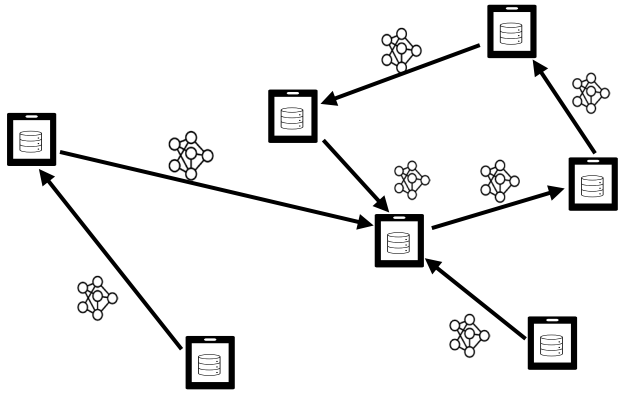
Current distributed learning schemes

Server-based architectures
(Federated Learning)



(single point of failure, poor scalability)

Server-less architectures
(Gossip Learning)



mainly on **static** settings
single connected component

What is Floating Gossip?

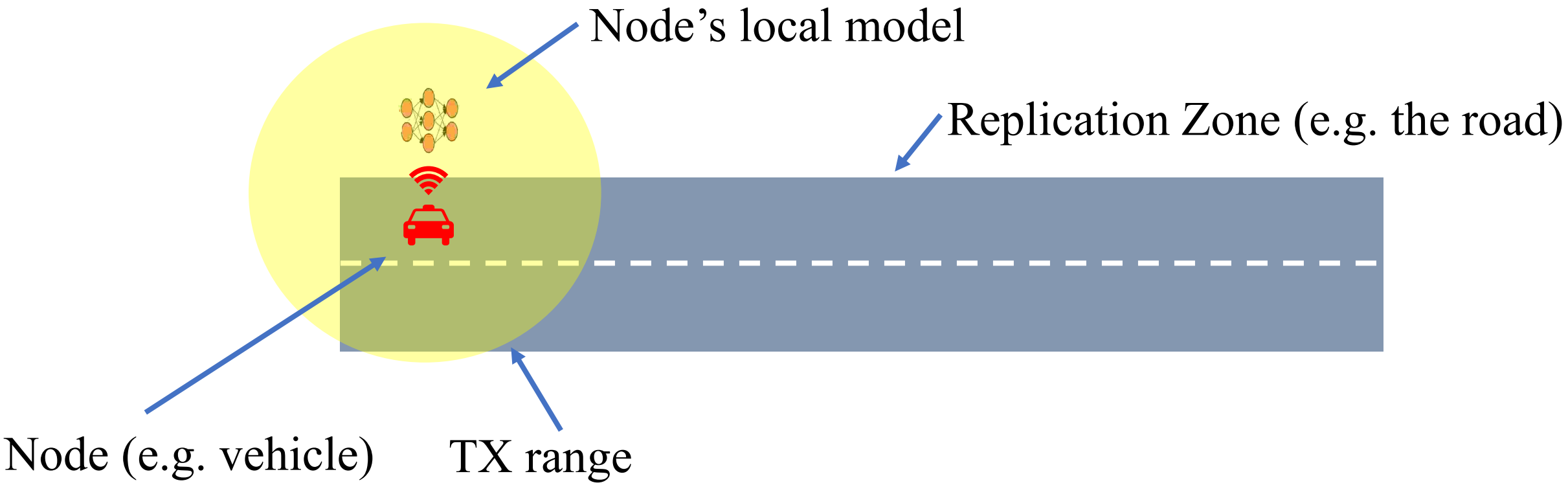
- A Gossip Learning scheme for dynamic scenarios
  - Tied to a specific region of space (Replication Zone, RZ)

- No infrastructure (in principle): Reliance on **gossip exchanges**
  - Data & model storage, and training are **probabilistic**

- **Goal**: Continual training of models over data from the RZ
  - Users are (typically) nodes themselves
  - Combination of static and moving nodes is ok

How does Floating Gossip work?

- When entering the RZ, each node has its own local (untrained) model
- As nodes move in the RZ, they collect data and incorporate it in their local model



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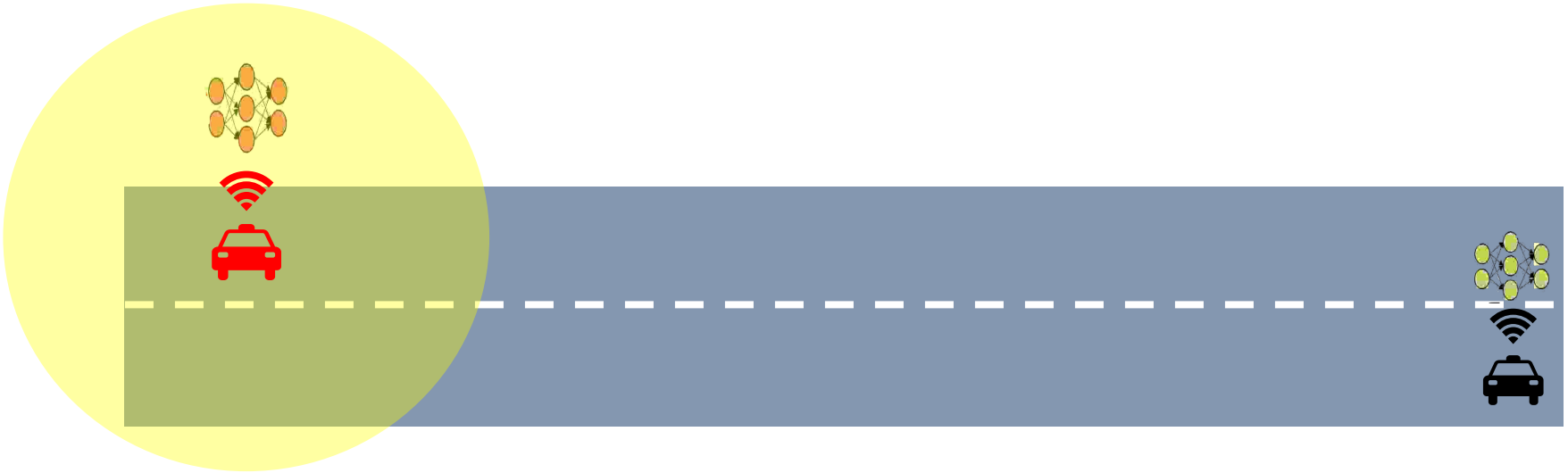
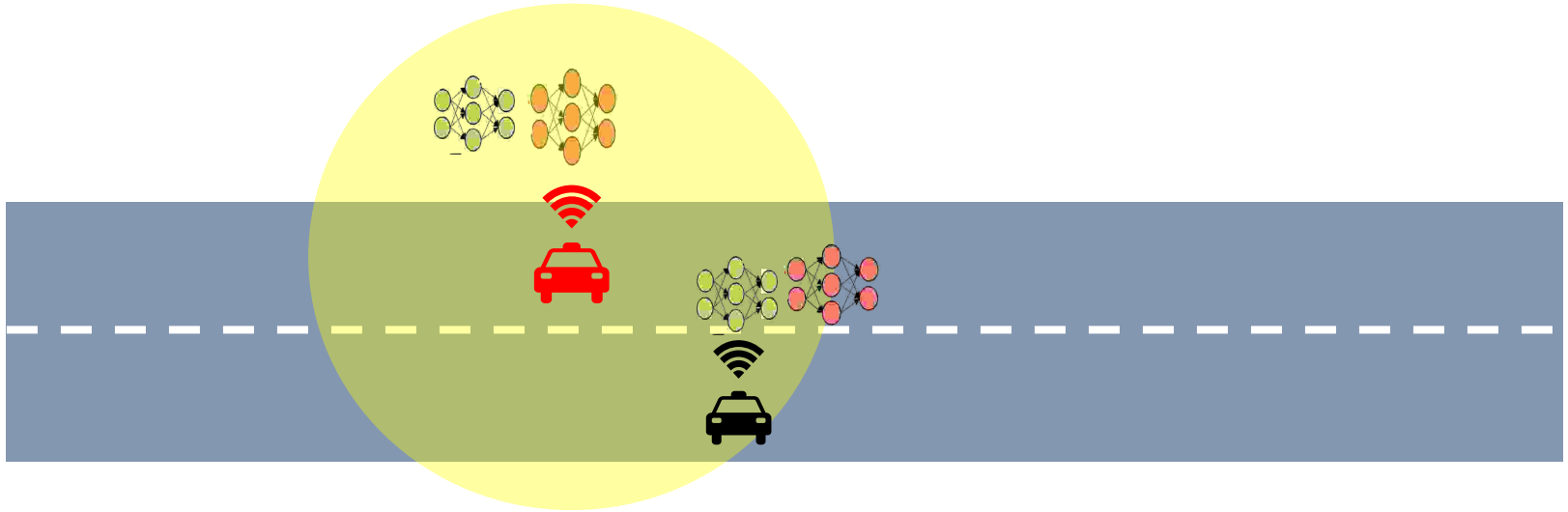


How does Floating Gossip work?

- At every contact **within the RZ**, nodes exchange opportunistically their local models
- Thus, models (and the information they incorporate) persist probabilistically in the RZ, even in presence of churn



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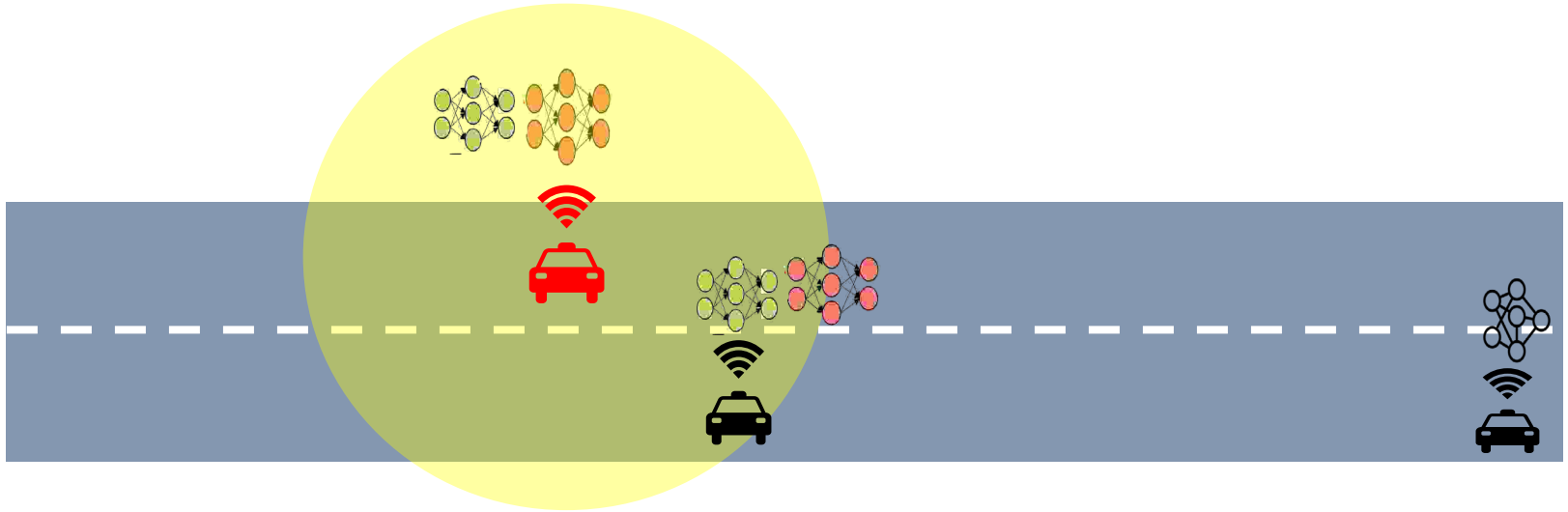

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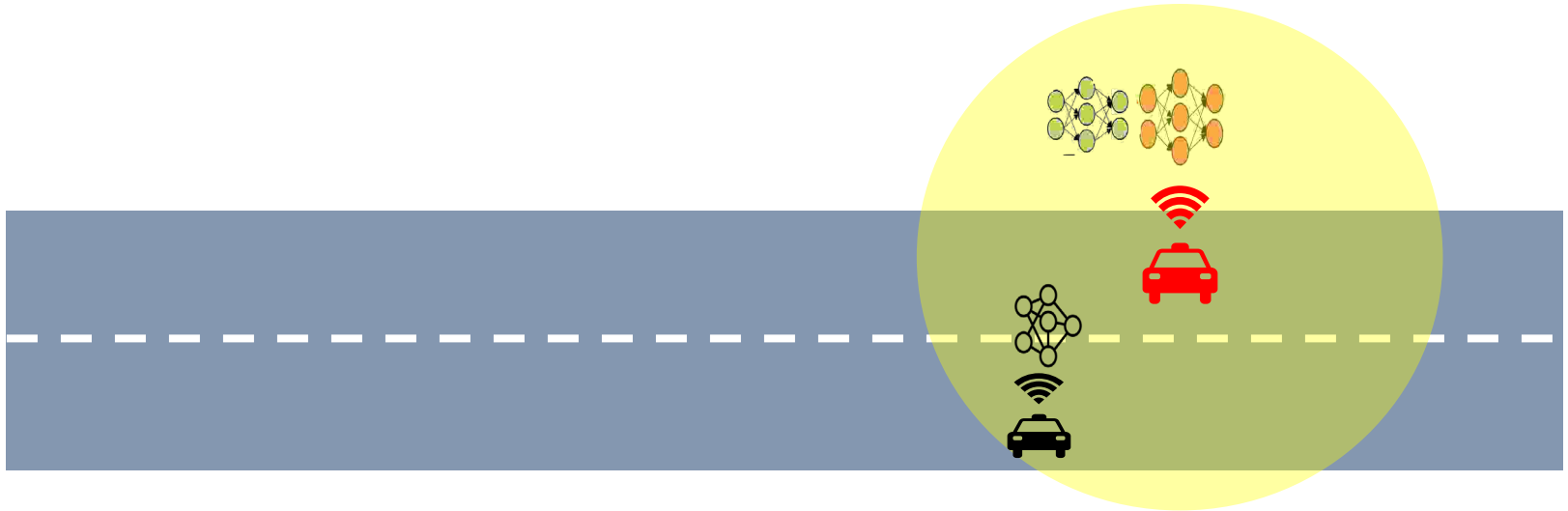

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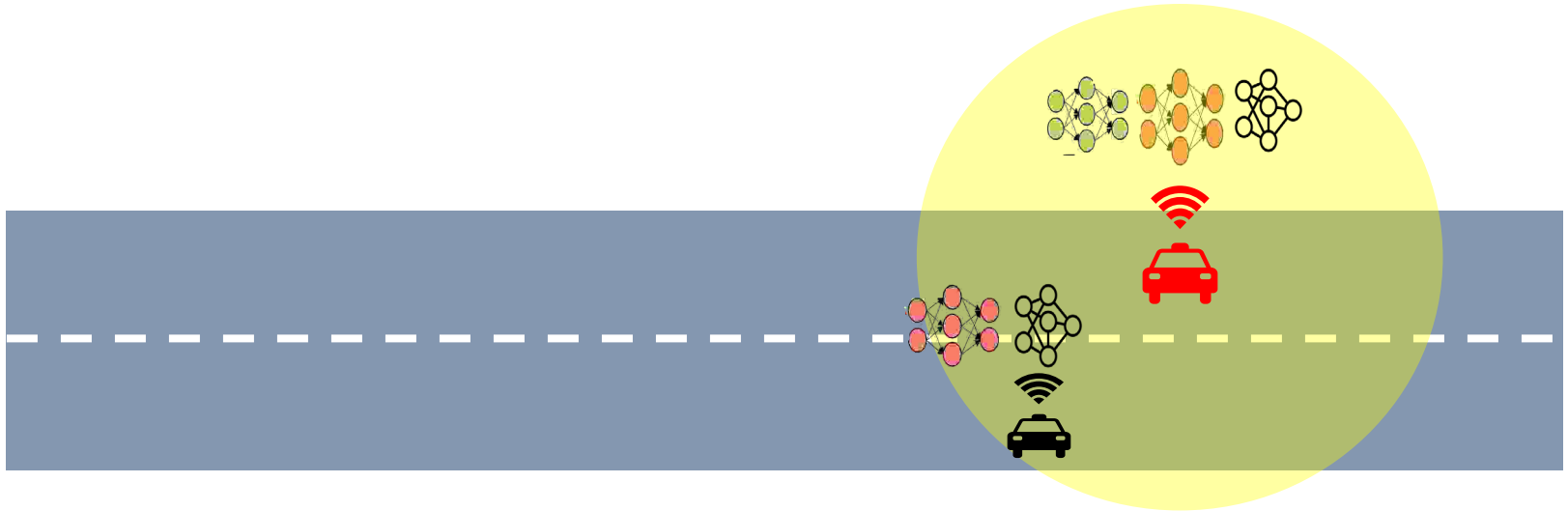
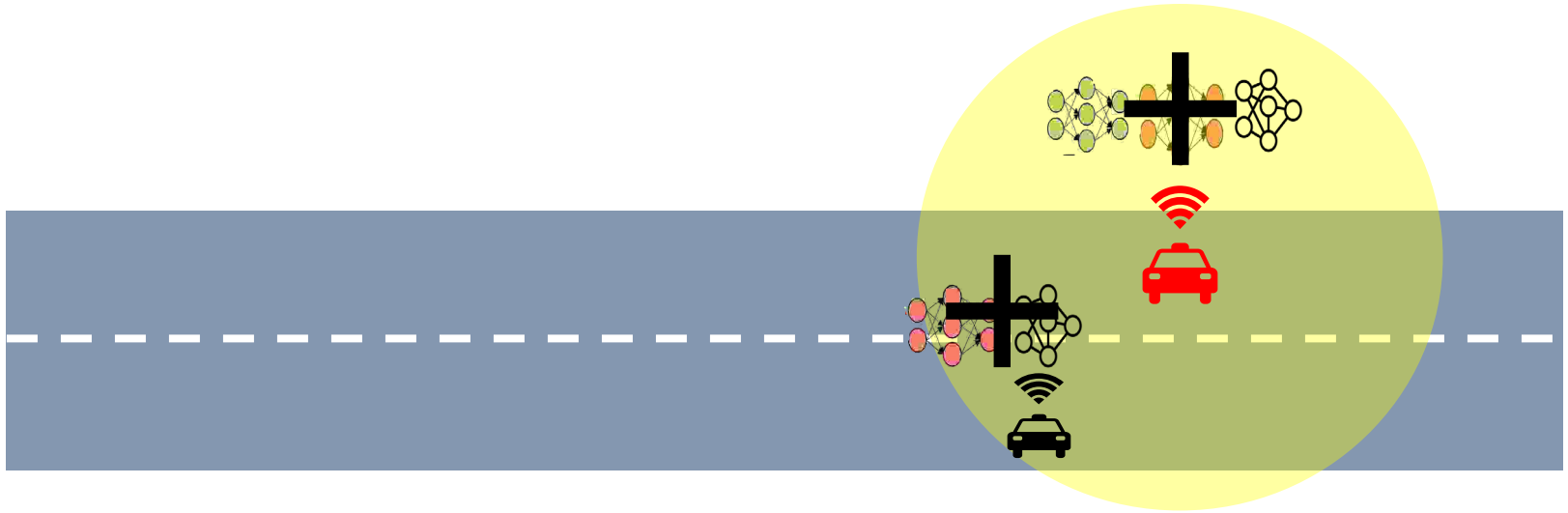


How does Floating Gossip work?

- Each node periodically **merges** its local model as well as all the received models
  - It creates a new local model (e.g. as an average of all models, as in FedAvg)
  - **Goal**: Improve performance of local model, via some form of knowledge transfer



When is Floating Gossip viable in dynamic scenarios?

- **Existing results**: Ad-hoc for specific learning architectures, task, and datasets

  ➡ **When is Floating Gossip viable?**

- Is it a **relevant** problem?

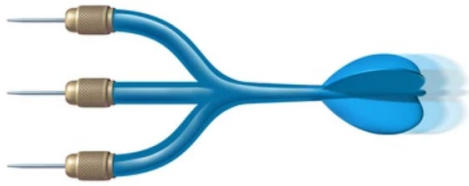
  - Edge is expanding towards user devices, and including moving devices

    ➡ **mobility matters!**

  - Floating Gossip is robust against churn and volatility

- **How does its performance compare to server-based approaches?**

Modeling FG performance: A three-pronged approach



- **Mean Field Theory**: Model ML model persistence and effects of mobility, and of communications efficiency
  - FC parameters: model availability
- **Classical Queuing Theory**: Model impact of computing load and communication dynamics on system stability and performance
- **Information theory**: Bounds on capacity of ML models
  - Maximum information which can be stored in a model, vs model size

System model

- Nodes moving on the plane
  - Homogeneous distribution in space
  - Same speed, communication technology
  - Perfect knowledge of position in space
  - **On entering the RZ**: each node possesses M **default models**

- Poisson arrivals of observations (data points) at nodes in the RZ
  - Intensity λ
  - Observations have a **finite** lifetime τ_l
  - They are incorporated in models via **local training**
  - They spread within the RZ via opportunistic model replication and **merging**

Model availability and observation availability

- **a:** Mean fraction of nodes who possess a model (**model availability**)
- **b**: Mean fraction of nodes who are busy exchanging models

$$\begin{cases} \dfrac{da}{dt} = \dfrac{b}{T_s(t)} a(1-a)S(t) + \lambda(1-a) - \alpha a \\ \dfrac{db}{dt} = 2g(1-b)^2 - \dfrac{b}{T_S(t)} - 2\alpha b \end{cases}$$

- DE obtained with mean field approach

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Nodes moving out of the RZ

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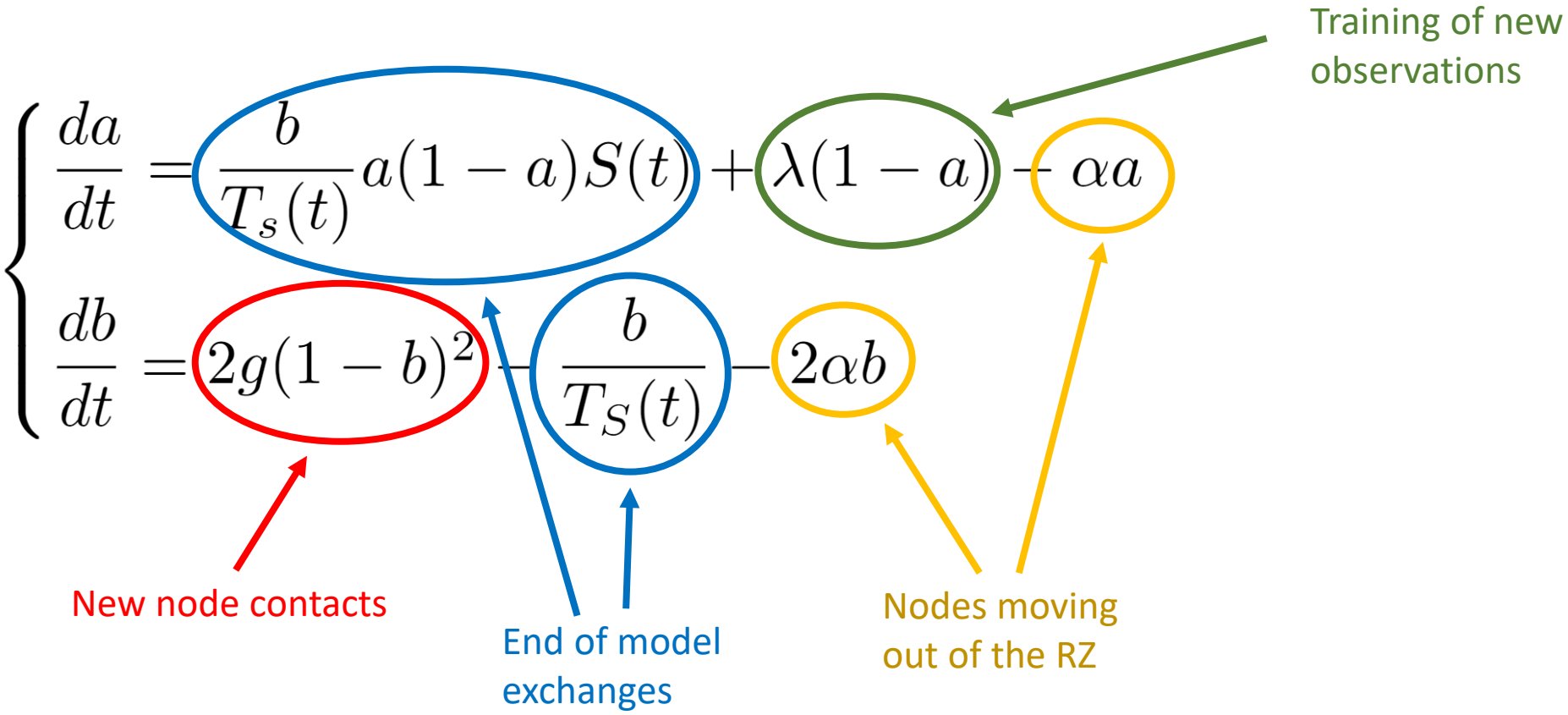

Model availability and observation availability

- **Observation availability o(t)**: Mean fraction of nodes with a model incorporating a given observation at time t

$$\frac{do(\tau)}{d\tau} = \frac{bS}{T_s}\left[(1-a)o(\tau) + ao(\tau - d_M)(1 - o(\tau - d_M))\right] - \alpha o(\tau)$$

$$o(\tau) = \begin{cases} 0 & \tau < d_I \\ \frac{1}{\lceil aN \rceil} & d_I \leq \tau \leq d_I + d_M \end{cases}$$

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Model merging

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The learning capacity measures Floating Gossip learning effectiveness

- **Floating Gossip Learning Capacity**: Maximum of the mean amount of information “stored” *in ML models*

$$\max_{M,L} \; a \min\left(\frac{L}{\lambda k}, \int_0^{\tau_l} o(\tau) d\tau\right)$$

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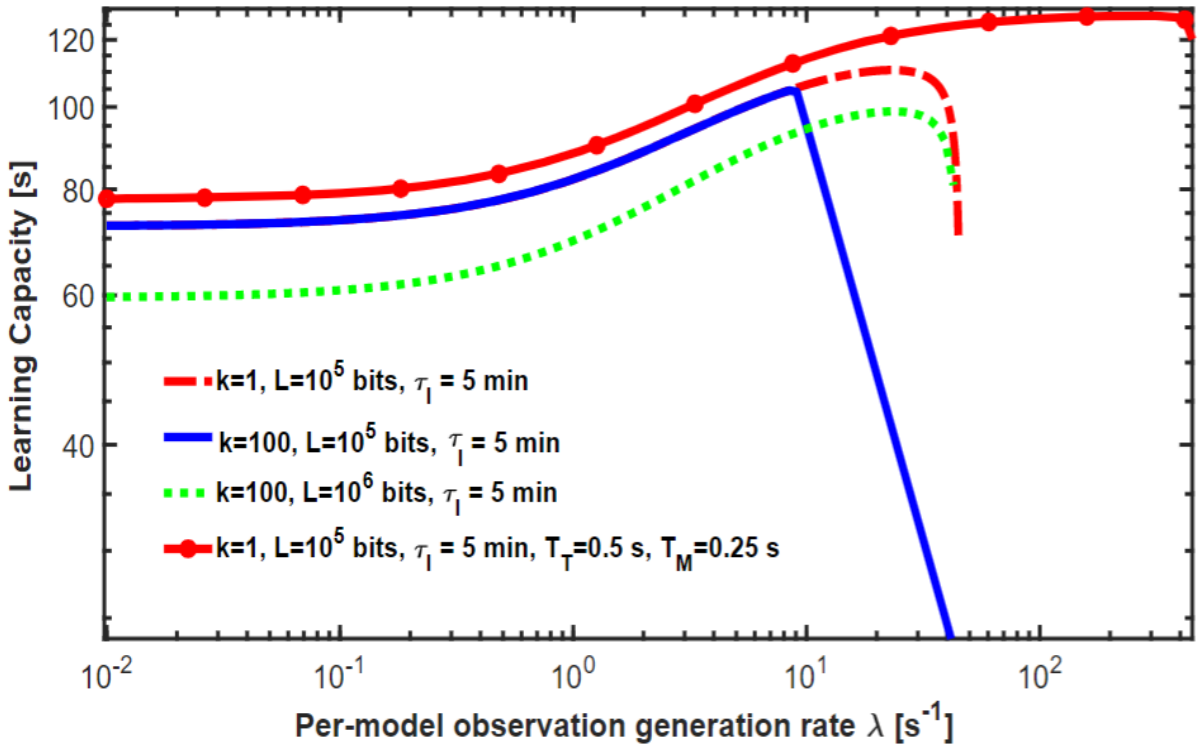
- ML model **capacity**: Amount of information it can "store"
  - Information theoretical upper bound
  - Key for accurate dimensioning, and for managing overfitting and forgetting

Numerical assessment

- Scenario and default values:
  - Random direction mobility model,
    - 0.5 m/s node speed
  - Circular RZ of radius 100 m
  - Training time: 5 s
  - Merging time: 2.5 s
- Assessment: both numerical and simulation (event-based)

FG thrives when learning load increases (but up to a point)



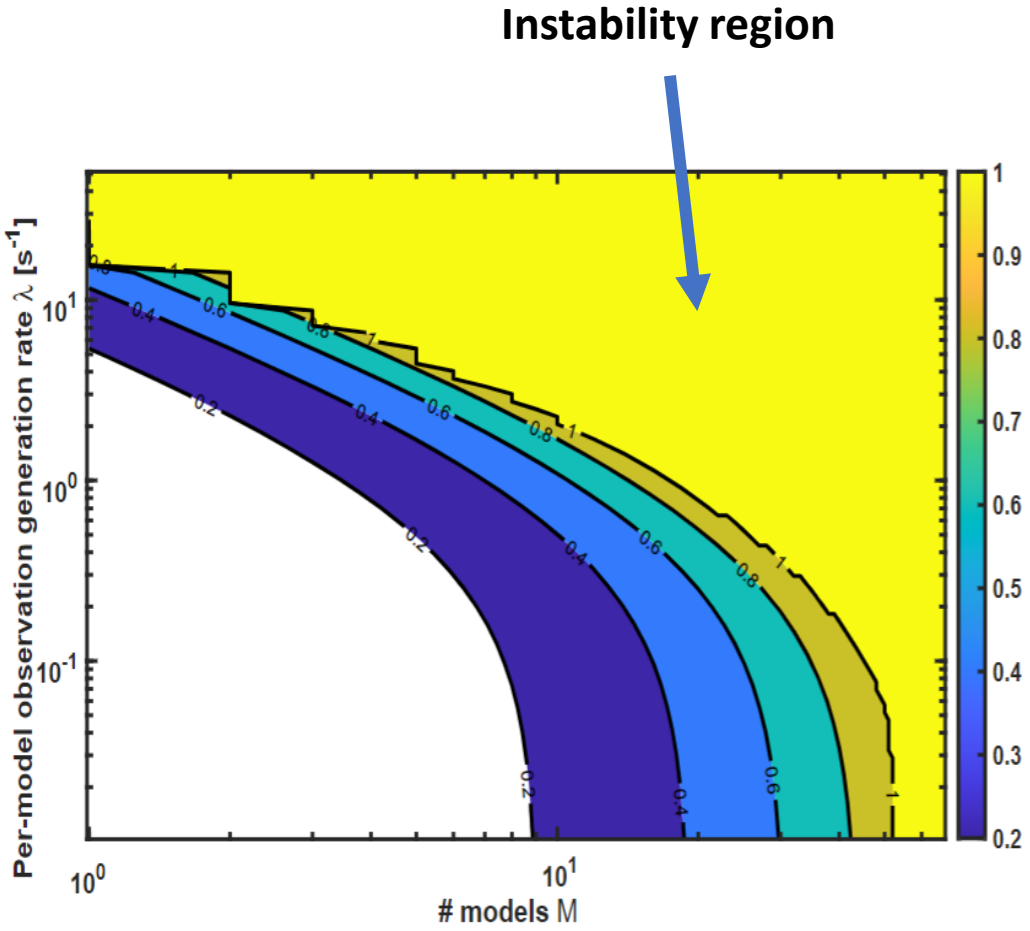
Increasing learning load has a **double effect:**

- It **increases learning capacity…**
  - Higher load means recruiting more nodes, expanding (probabilistically) service capacity
- …but it **brings the system closer to instability**

(system equivalent to catastrophic forgetting)

- Need for accurate system dimensioning to maximize efficiency as a function of the learning load

FG Learning capacity limited by the aggregate computing capacity of the collaborative system



- Tradeoff between **number of models** to train, **model size**, and **learning load**

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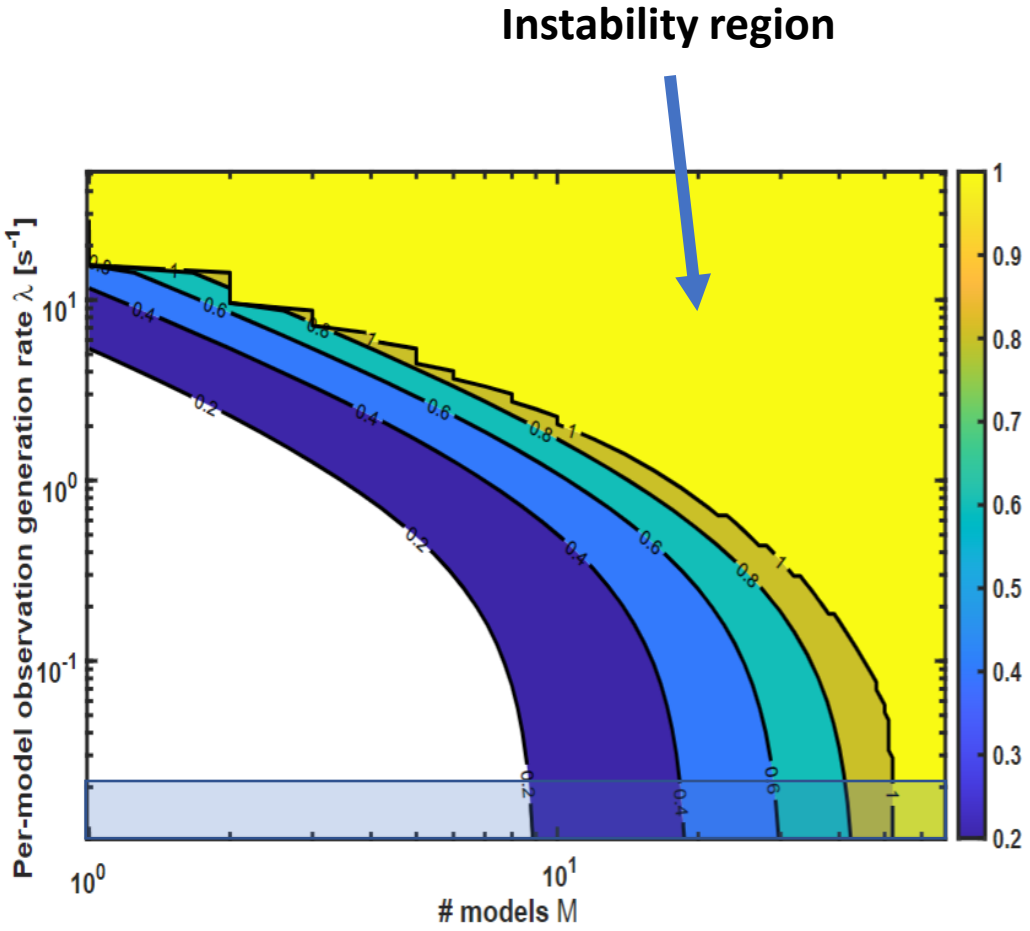

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- **Model-limited regime**:

Limit performance depends on the effectiveness of gossip-based model exchange

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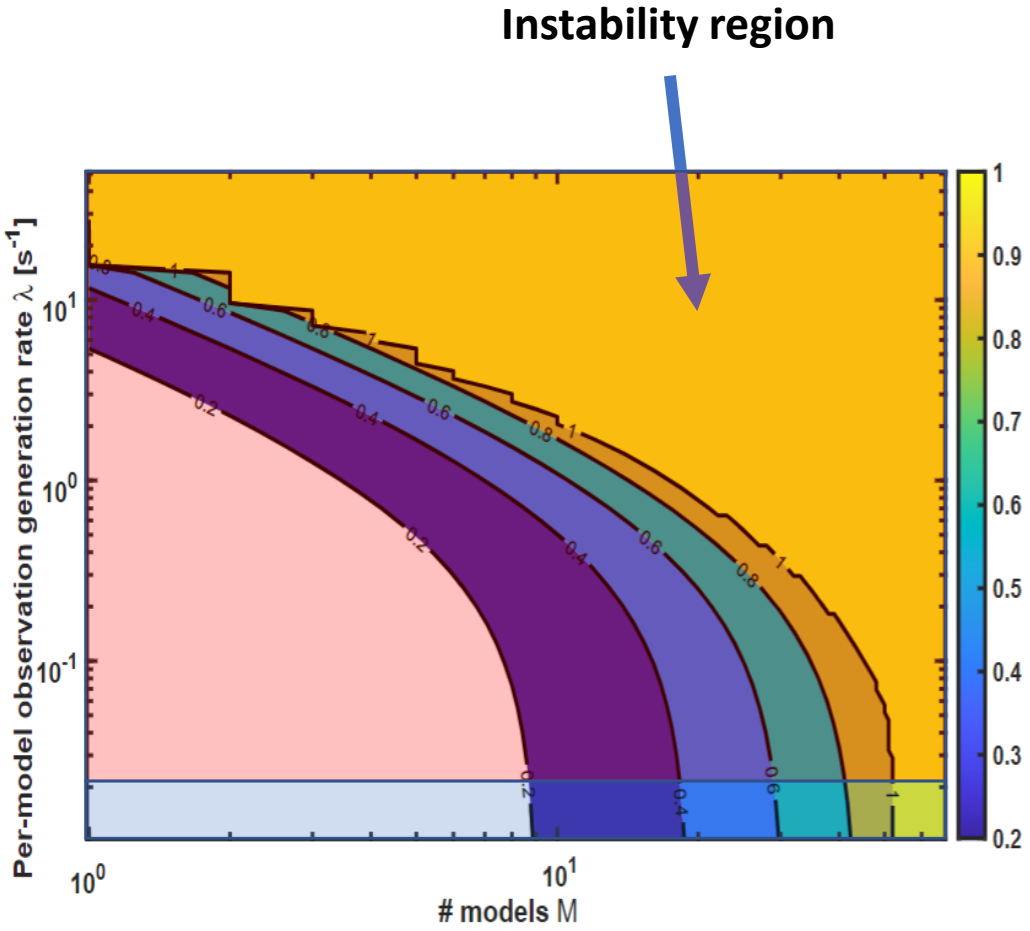

- Tradeoff between **number of models** to train, **model size**, and **learning load**

- **Model-limited regime**:

  Limit performance depends on the effectiveness of gossip-based model exchange

- **Computing-limited regime:** Limit performance depends on node's computing capacity

How fresh is the information incorporated in ML models via Floating Gossip?

Three regimes:

- **Low learning load**: Staleness increases with load (but it remains low)

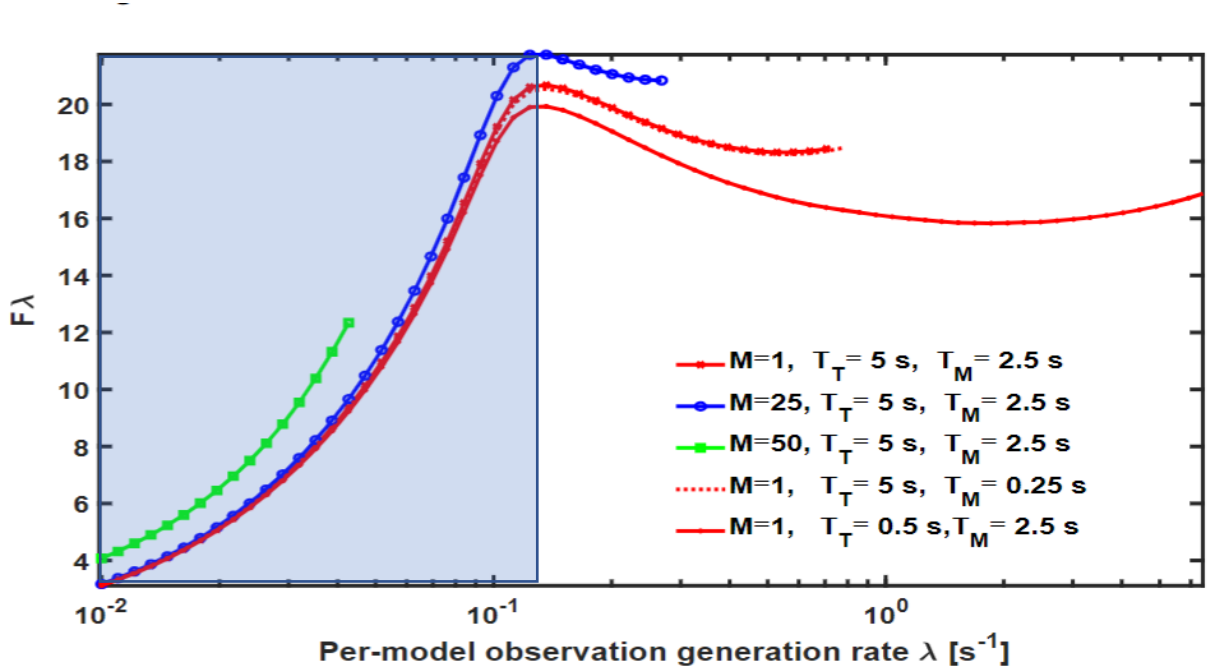

Fig. 4: Ratio of model staleness F over per-model mean observation interarrival time $1/\lambda$, versus per-model observation generation rate λ. Observation lifetime is $\tau_l = 300$ s, $k = 1$, with model size $L = 10$ kb.

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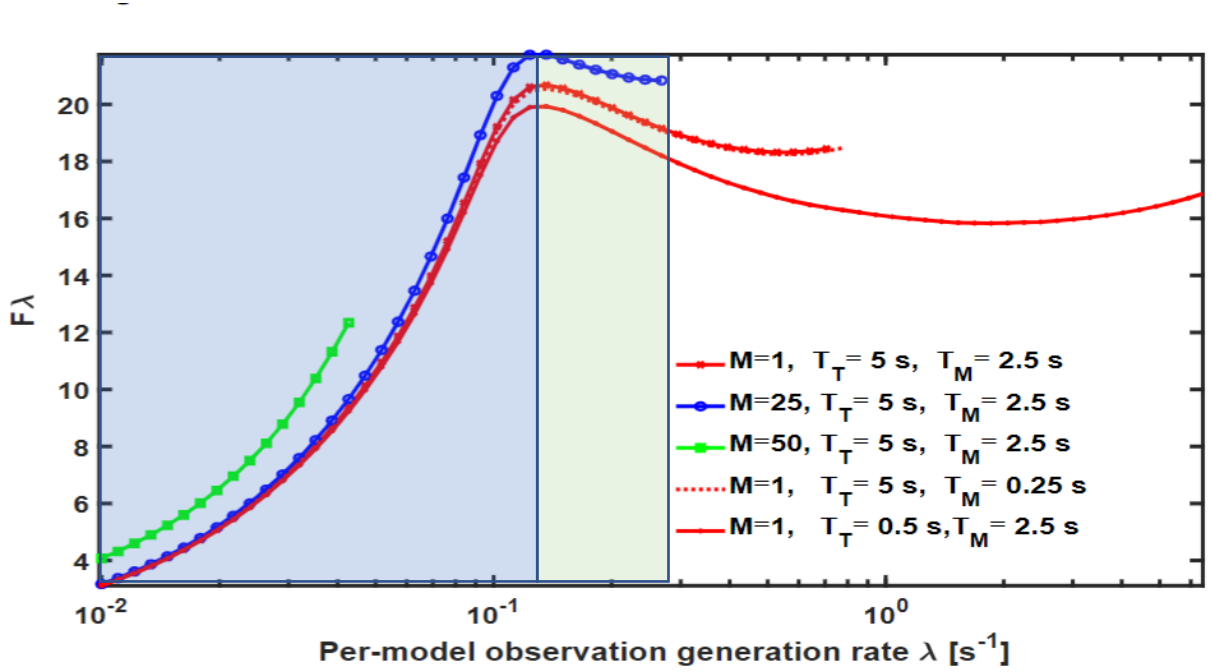
- **High learning load:** (close to system saturation): The system incorporates fresher information



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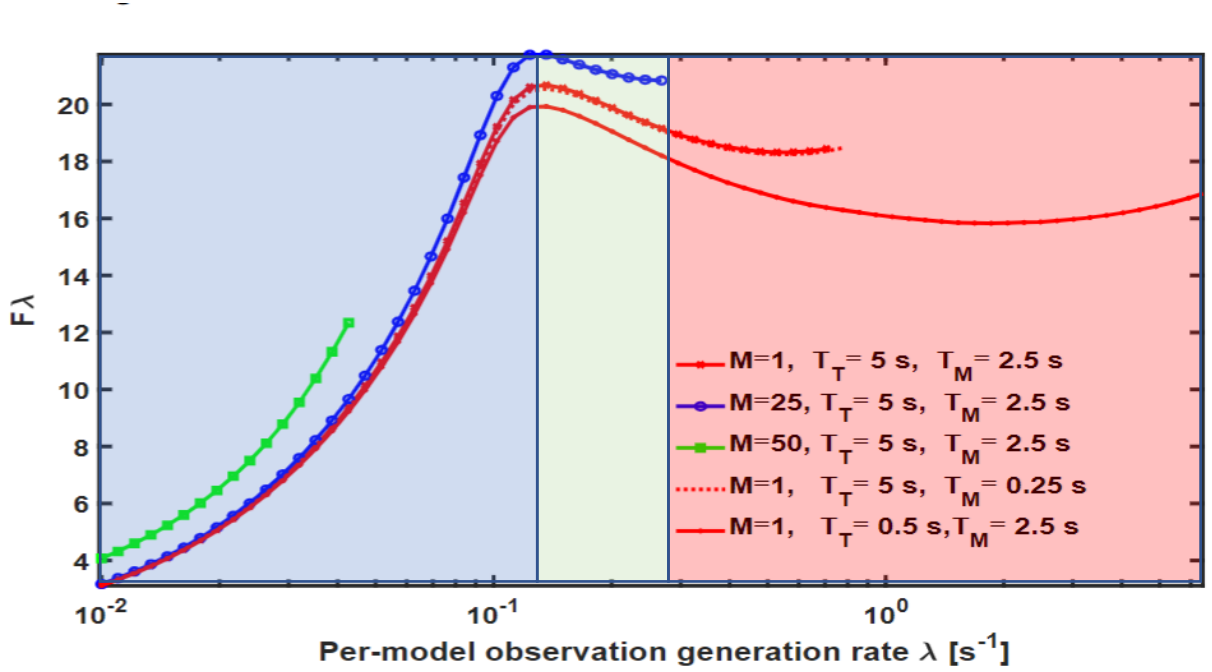
How fresh is the information incorporated in ML models?

Three regimes:

- **Low learning load**: Staleness increases with load (but it remains low)
- **High learning load:** (close to system saturation): The system incorporates **fresher information**
- **Instability**

Increasing the n. of models to train brings to an earlier onset of instability, but with marginal impact on staleness (**scalability**)



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Conclusions and future work

We proposed a framework for a first-order characterization of the performance of Floating Gossip

- A fully distributed, gossip-based learning scheme
- Performance patterns vary significantly from centralized, non collaborative learning schemes

Floating Gossip can be very effective in implementing fully distributed, cooperative continual learning schemes

- Very robust to node churn and mobility (and thriving on it)
- Scalable
- Performing better on high loads
- Limited by the aggregate of the computing resources of all nodes, and by gossip-based information diffusion

Future work: Heterogeneous scenarios

Thanks!

Questions: gianluca.rizzo@hevs.ch