

# NDN for AI and AI for NDN: challenges, opportunities and early results

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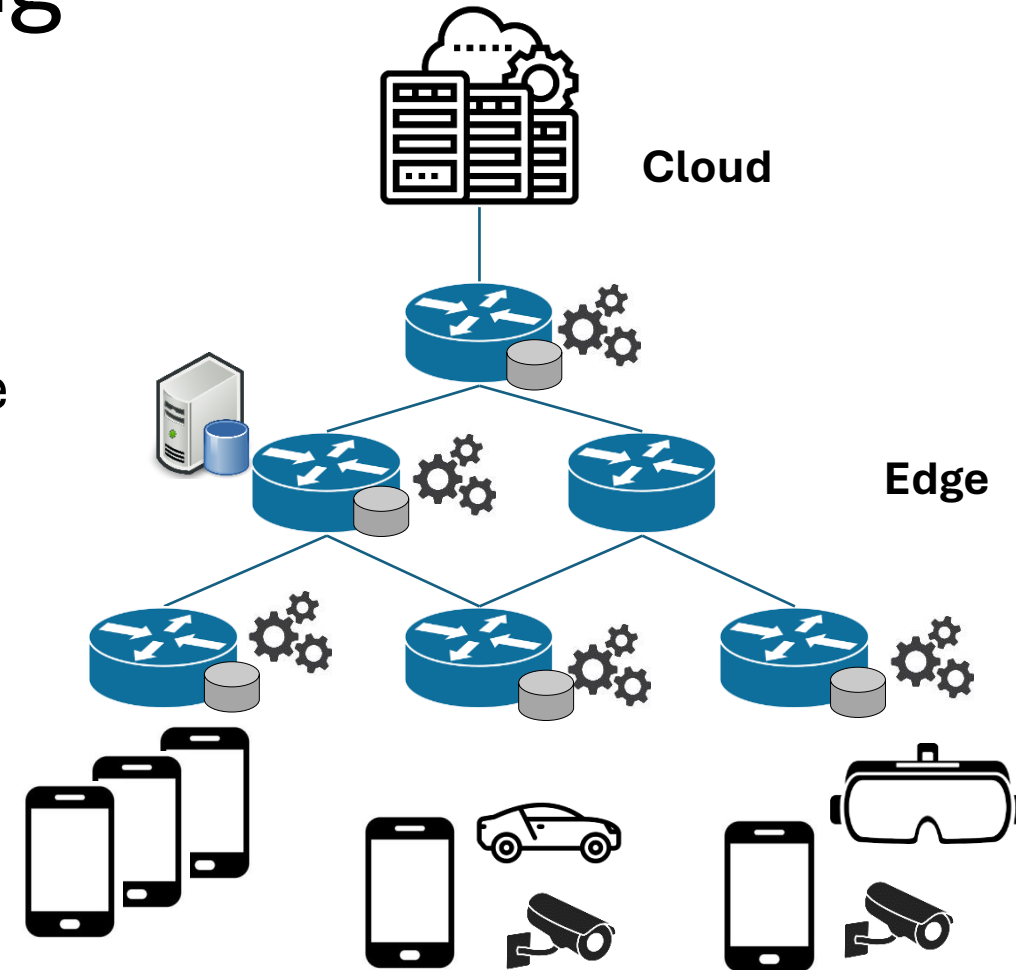
# Outline

- **Two complementary perspectives on the NDN ↔ AI interplay**
- **NDN for AI**
  - AI applications are content-centric
  - NDN benefits
  - Early results: the case of Federated Learning and split inference
- **AI for NDN**
  - AI can improve NDN content discovery and delivery
  - Semantic-aware NDN forwarding
  - Early results: The case of vehicular crowdsensing

# NDN for AI

# Distributed AI and networking

- Distributed AI is moving at the network edge:
  - Federated Learning, Edge AI, Split inference
- AI applications increasingly require networking support beyond packet forwarding
  - In-network computing
- The network is now a bottleneck
  - The current Internet remains host-centric



# AI applications are content-centric

- Distributed AI exchanges:
  - models, embeddings, inference results...
- These are naturally named data objects
- AI workflows are iterative, content-centric, and cache-friendly

**Yet, the network is still host-centric!**

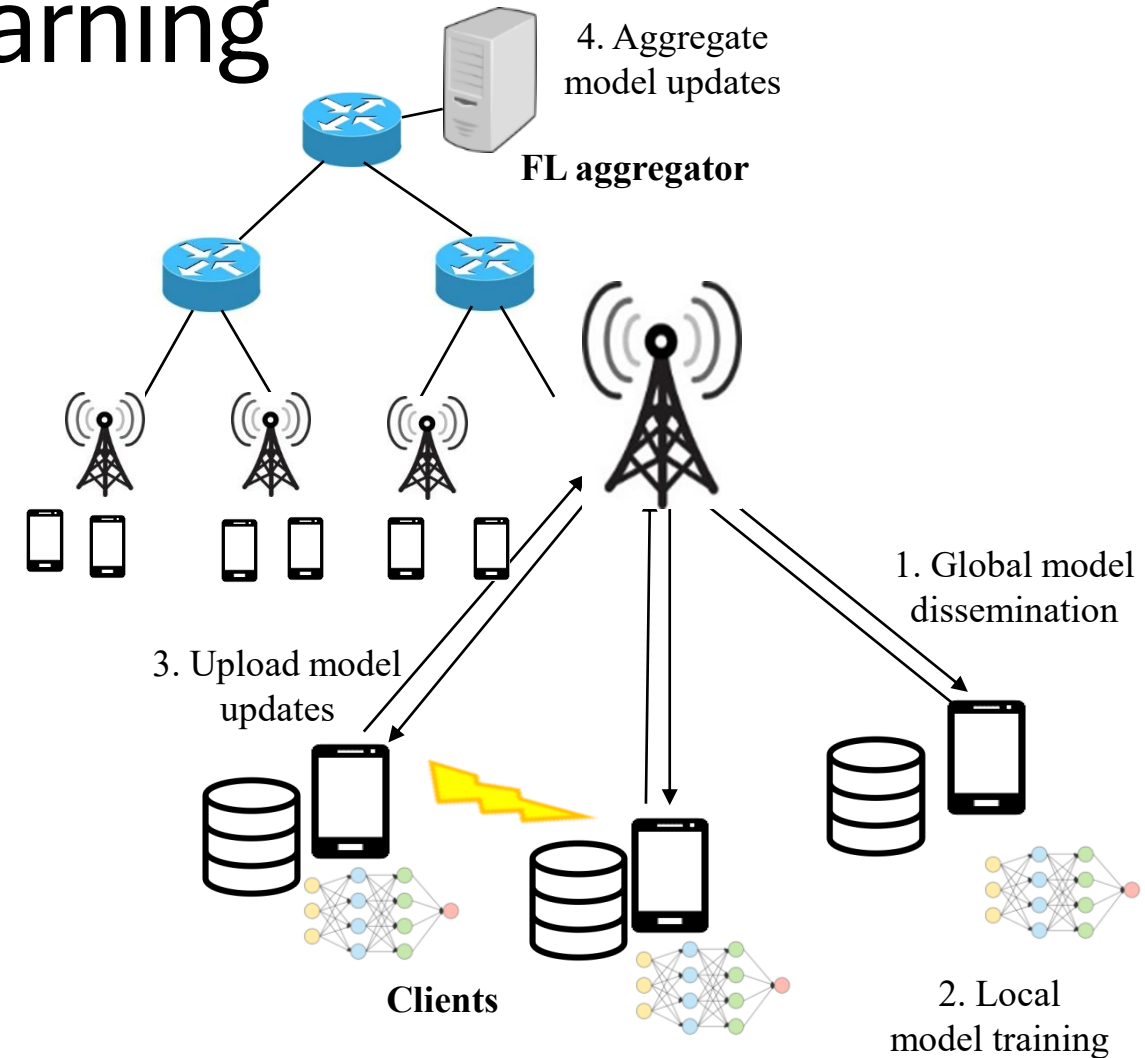


# NDN as an enabler of distributed AI

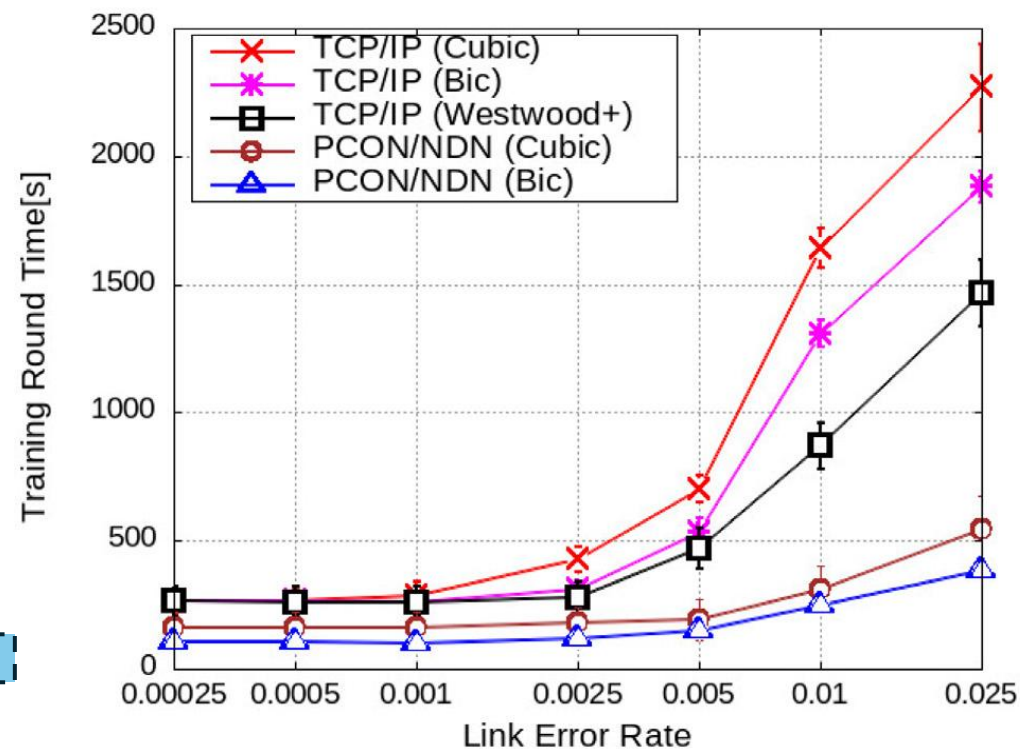
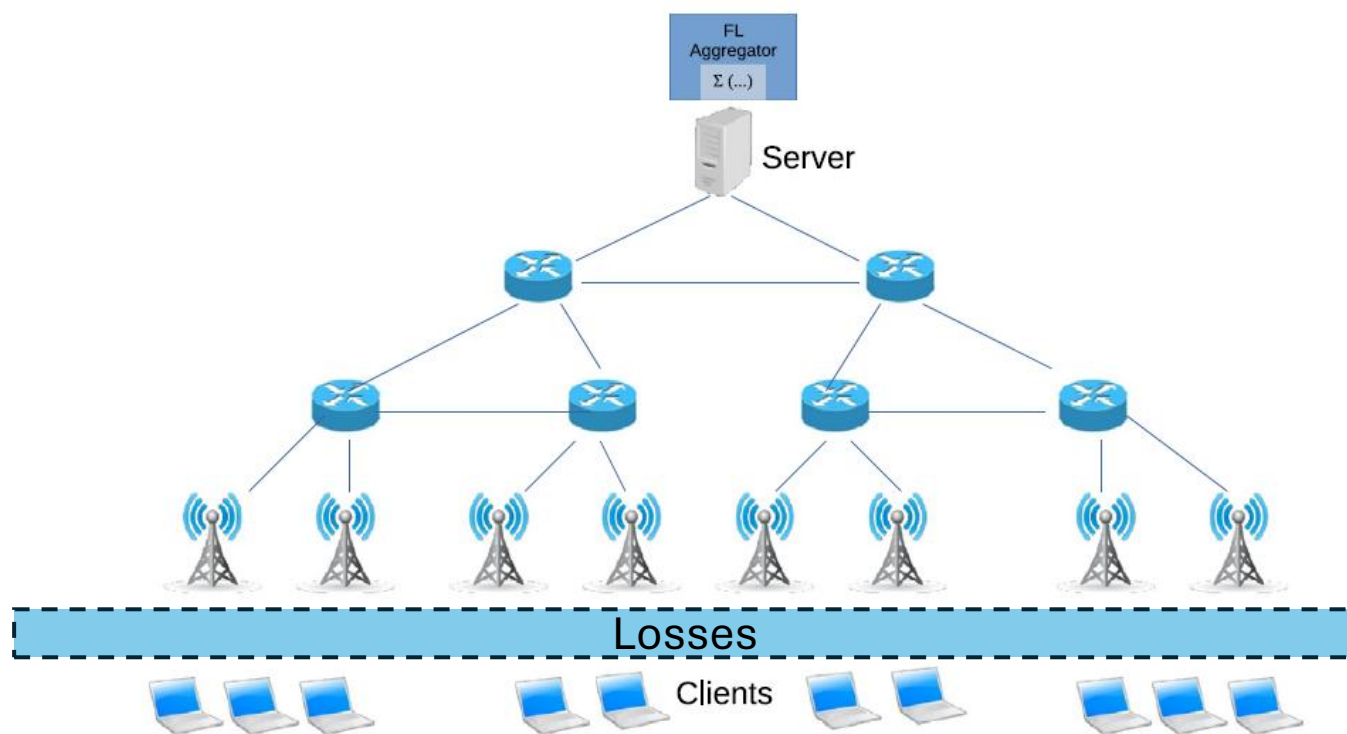
NDN Feature	Benefits
<b>Name-based delivery</b>	AI tasks, models, inputs, and inference results can be identified by name, independently of the host. In-network processing is facilitated
<b>In-network caching</b>	Models and results can be served by nearby caching nodes, reducing latency and increasing resiliency to losses
<b>Multicast support</b>	Efficient distribution of models and results to many clients at the same time
<b>Stateful forwarding</b>	Fast recovery in presence of packet losses
<b>Security by design</b>	Integrity, authentication, and provenance of models, and inference results

# The case of Federated Learning

- FL systems assume:
  - end-to-end communication
  - no in-network computing
- Convergence depends on the slowest client (straggler issue)
  - Lossy wireless links increase round duration
  - End-host retransmissions preserve reliability but add delay
  - Excluding stragglers hurts model accuracy



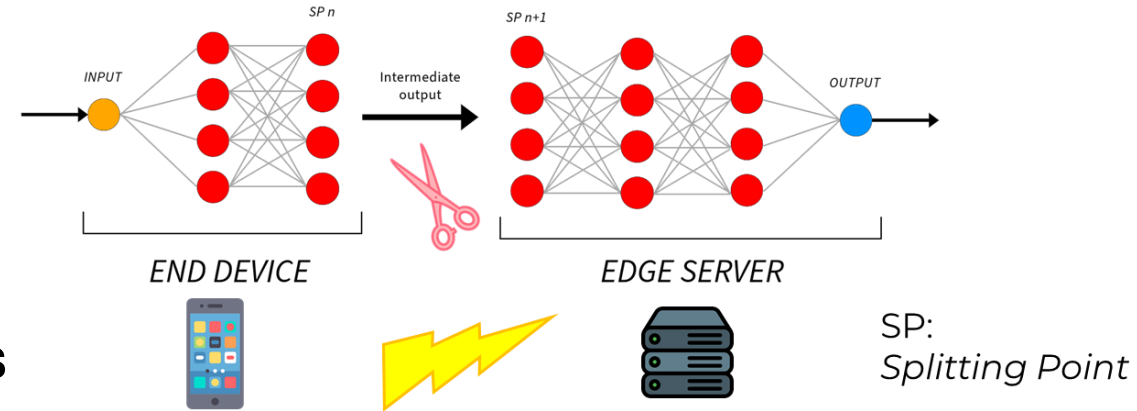
# Improving FL via NDN



## PCON (Practical CONgestion control) + NDN vs TCP/IP

# Improving Split Inference with NDN

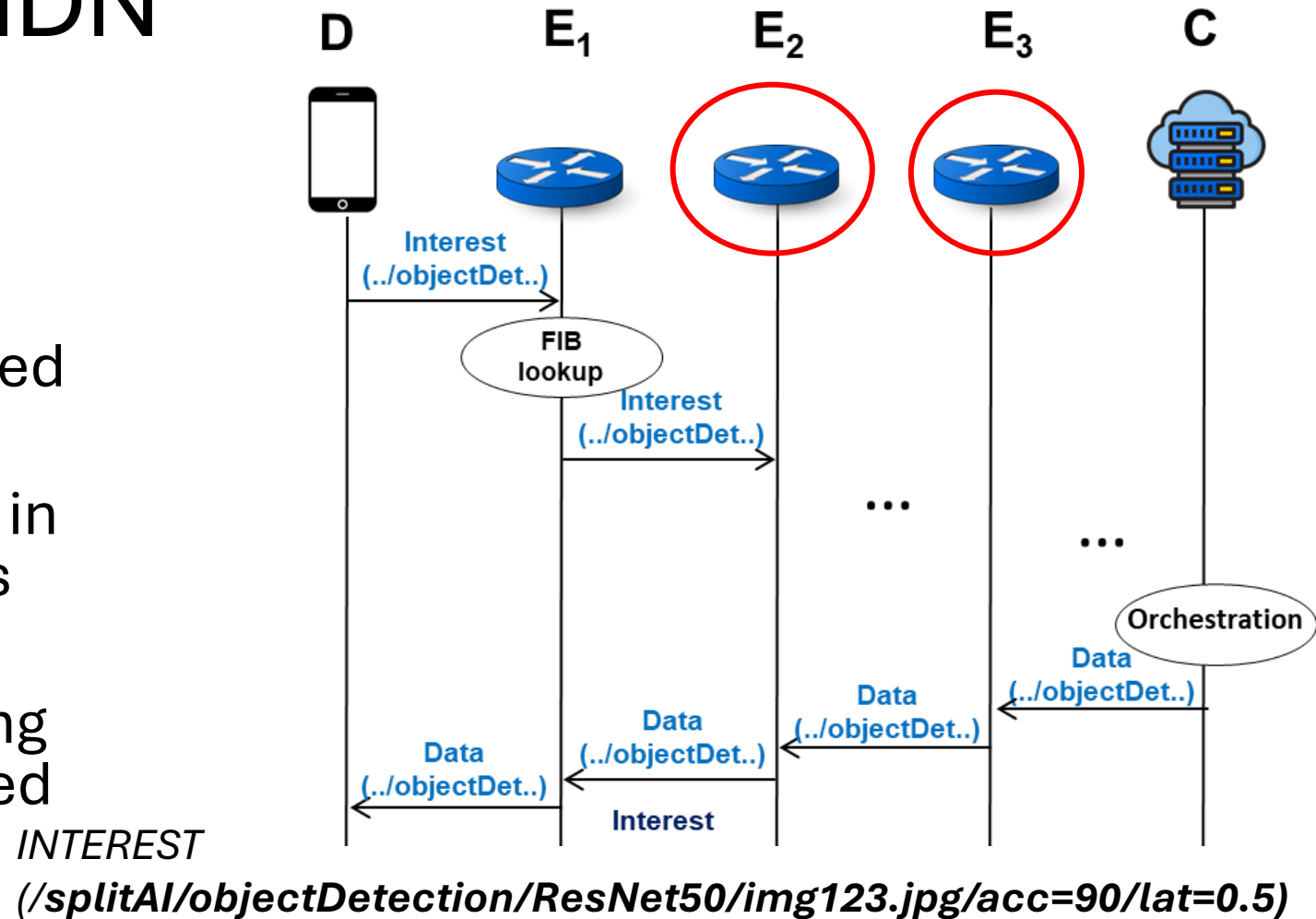
- Split Inference splits Deep Neural Networks (DNN) across multiple nodes to improve efficiency and reduce the burden on individual devices
  - The inference task is partitioned across multiple in-network nodes
- Input data, intermediate outputs and inference results to be transferred quickly and reliably



# Split inference via NDN

## Discovery stage:

- Clients issue an inference request through an augmented Interest
- On-path edge nodes look up in the FIB and can candidate as executors
- The cloud decides the splitting strategy and instructs selected nodes

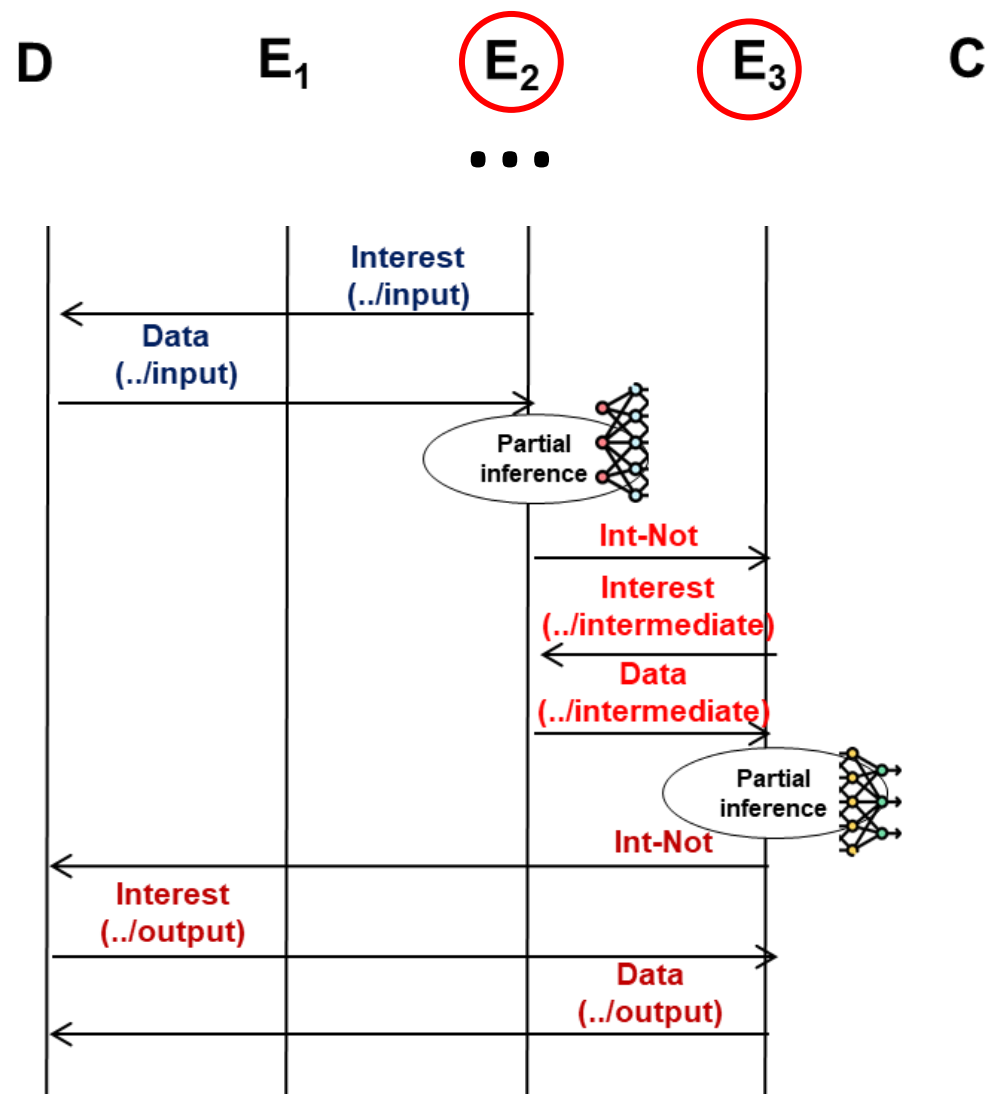


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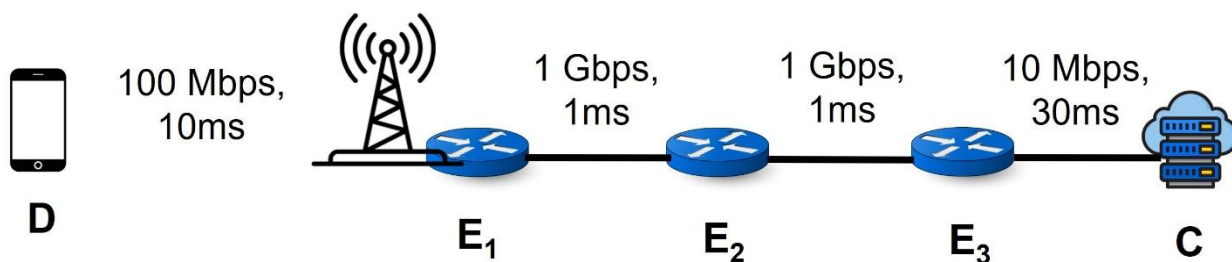
# Split inference via NDN

## Data exchange

- Selected nodes retrieve the (input/intermediate output) data upon which executing their part of the DNN
- Upon completion, each selected node issues an Interest Notification (*Int-Not*) message to signal that the intermediate output/inference results is ready
- Data can be lost
  - Thanks to native NDN in-network caching intermediate nodes can help recover losses

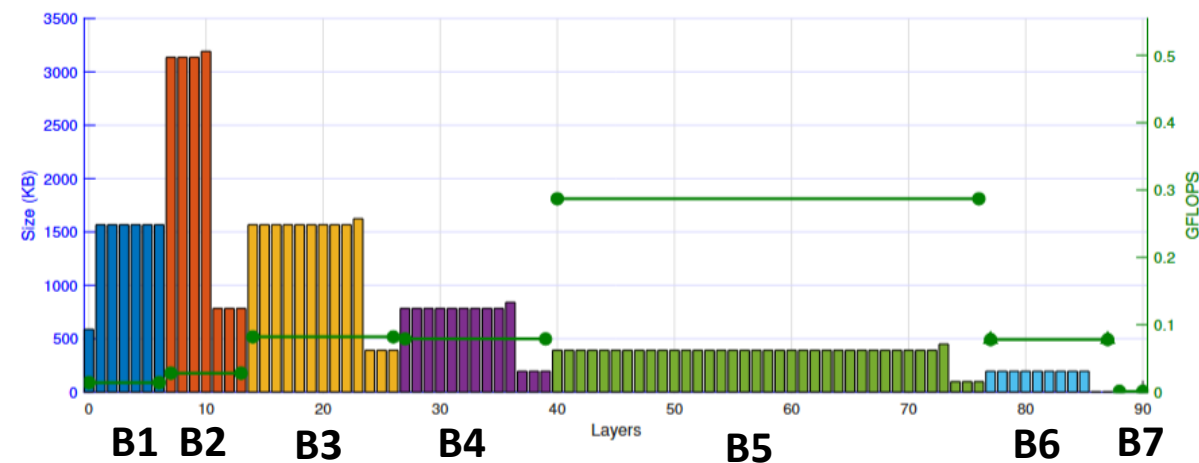
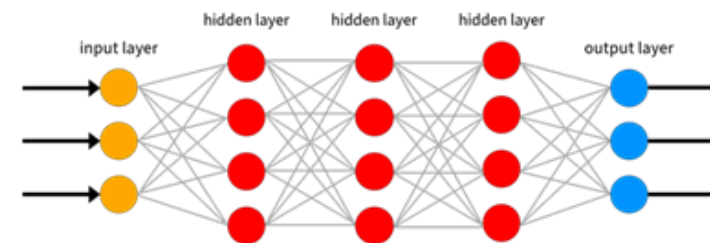


# Split inference via NDN



**ns-3** NETWORK SIMULATOR + **ndnSIM**

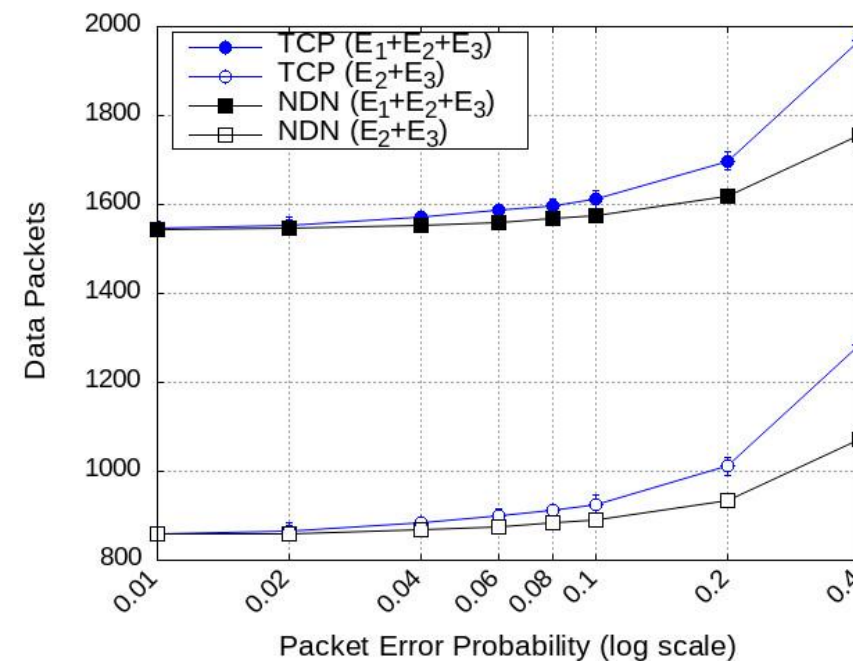
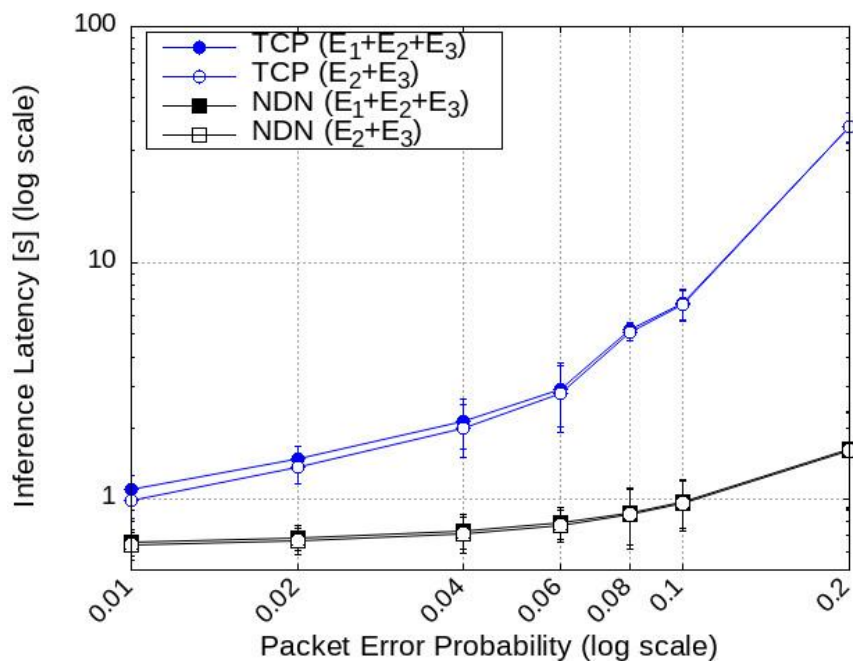
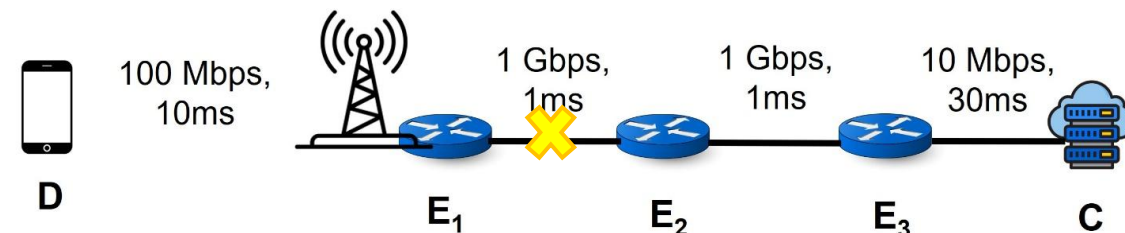
- Chain topology with 5 nodes
- DNN model: MobileNetV1 divided into 7 consecutive blocks
- Input data size: 330 kB



# Split inference via NDN

## TCP VS NDN

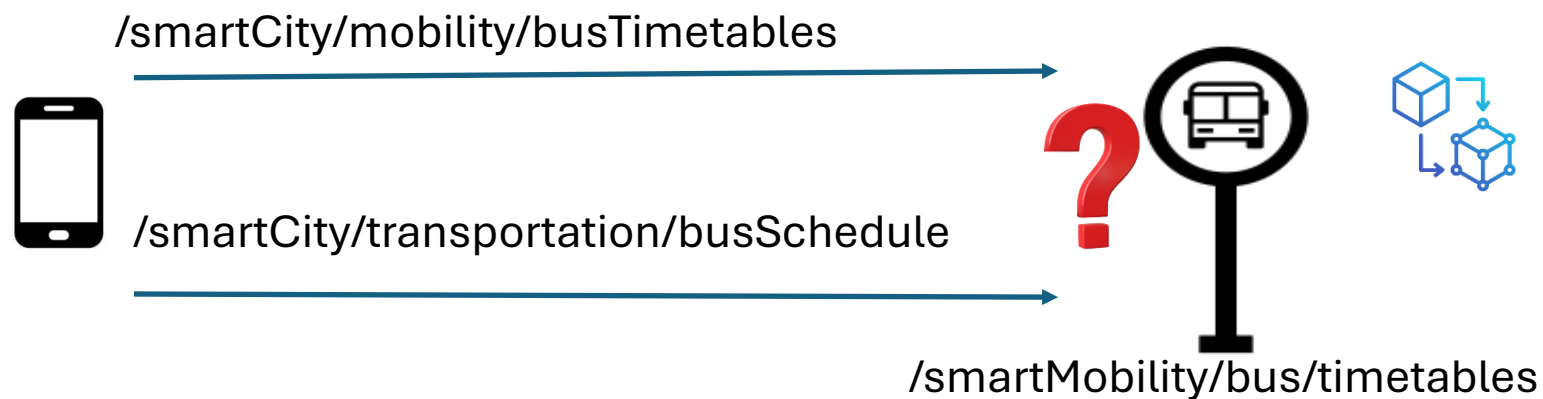
- Distinct split strategies
- A client asks for a DNN task
- Input data size: 330 kB



# AI for NDN

# Limitations of name-based lookups

- NDN relies on exact name match lookups
- But naming conventions may vary across data producers
- **Semantically equivalent data can have different names!**
- **We need a flexible data discovery solution**

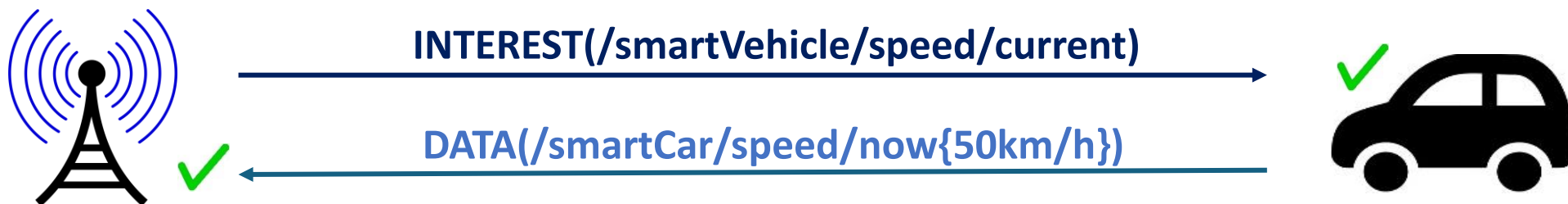


Idea:  
**semantic  
awareness** in the  
NDN forwarding  
fabric

# Augmenting NDN with semantic intelligence

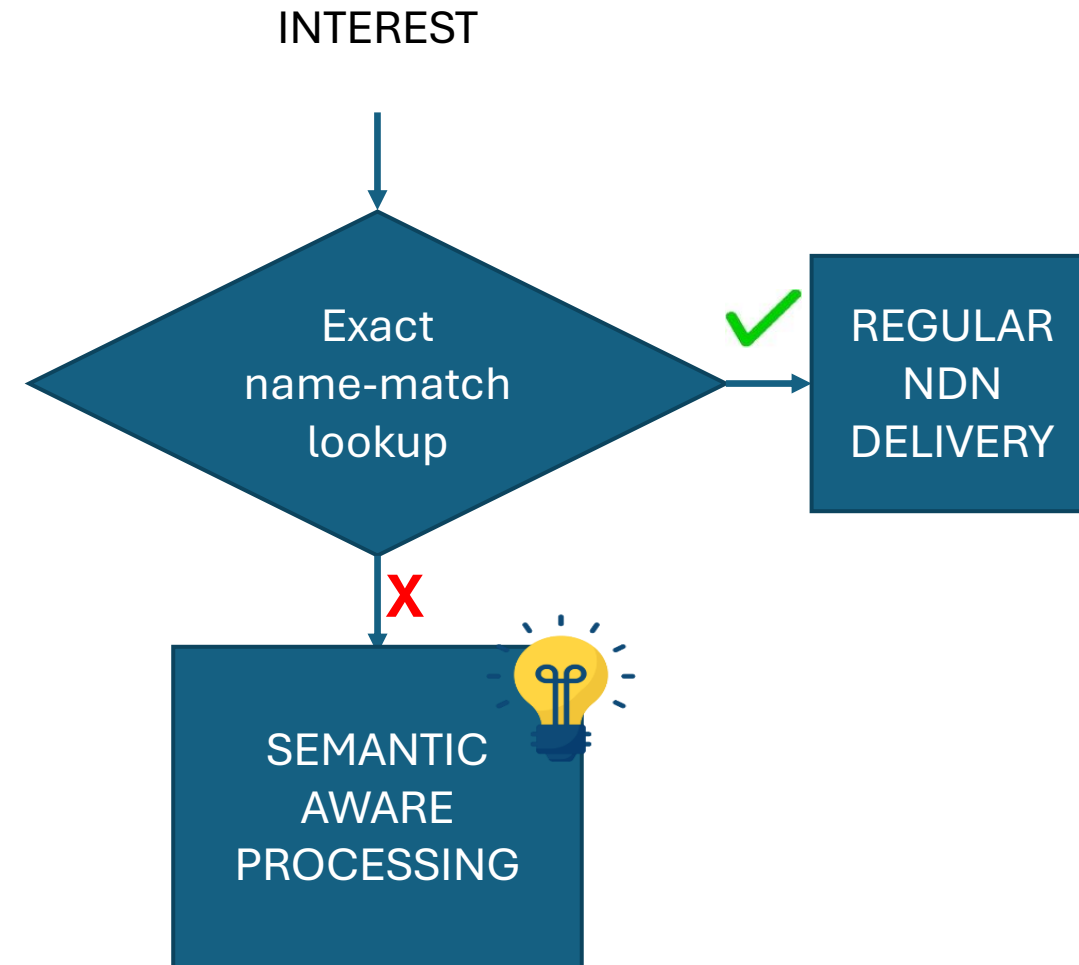


- A mechanism allowing NDN nodes to understand name semantics
- Implementing flexible name matching among different hierarchical names
  - We can use Natural Language Processing (NLP) mechanisms!
- First work: K. Chan, B. Ko, S. Mastorakis, A. Afanasyev, and L. Zhang, “Fuzzy interest forwarding,” in Proc. 13th Asian Int. Eng. Conf., **2017**, pp. 31–37
  - single-component name matching, using Word2Vec to generate vector-based representations of name components and applying cosine similarity to measure their semantic closeness.



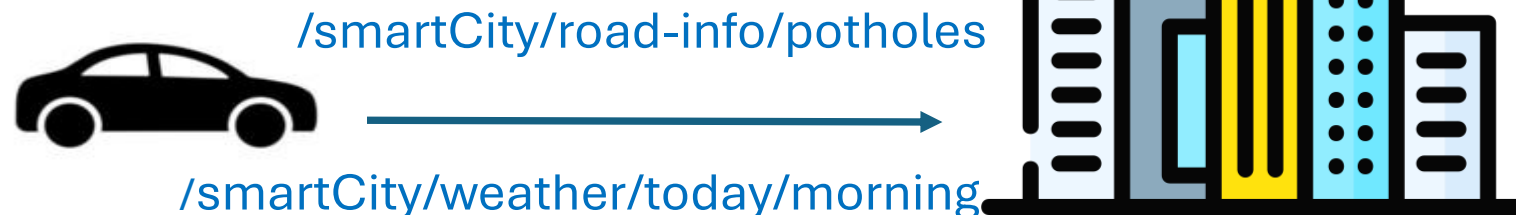
# Augmenting NDN with semantic intelligence

- We embed deep learning-based semantic recognition models into the NDN forwarding fabric.
- When an incoming data request fails to be solved with exact name matching, our approach looks for the **semantic similarity between the name in the Interest and the name of available data in the NDN tables**.
- This allows to discover and access data that are semantically similar, even when naming conventions differ.



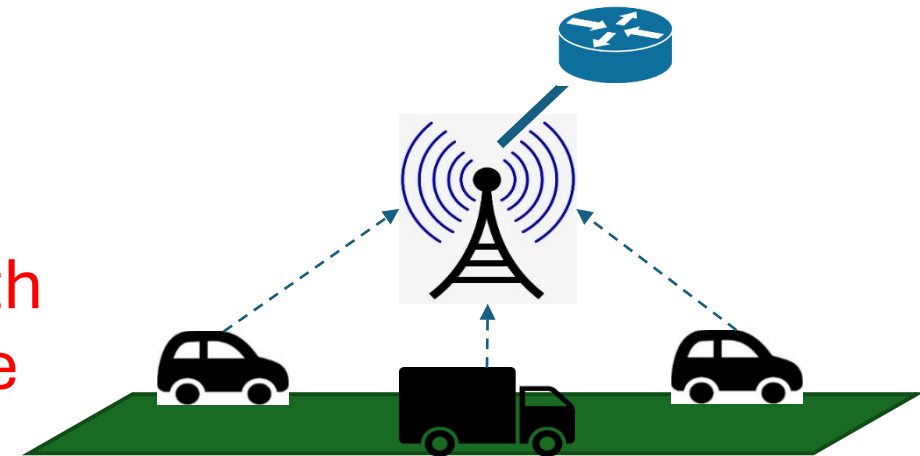
# Discovering smart-city services

- Names are converted into embeddings (i.e., vectors) and compared in a multi-dimensional space
- Embeddings generation is based on pre-trained **Sentence Transformers models**, e.g., All-miniLM-L12-v2 (348-dimensional vector space, 12 layers), All-miniLM-L6-v2 (348-dimensional vector space, 6 layers), designed for fast semantic recognition tasks
- Name embeddings pre-computed when filling FIB and CS at the producer side



# The case of vehicular crowdsensing

- Collecting named data with NDN:
  - ✓ Vehicles' identity a priori unknown
  - ✓ Handling mobility
  - ✓ Data can be retrieved from vehicles with different manufacturers, different home countries -> Naming conventions may vary



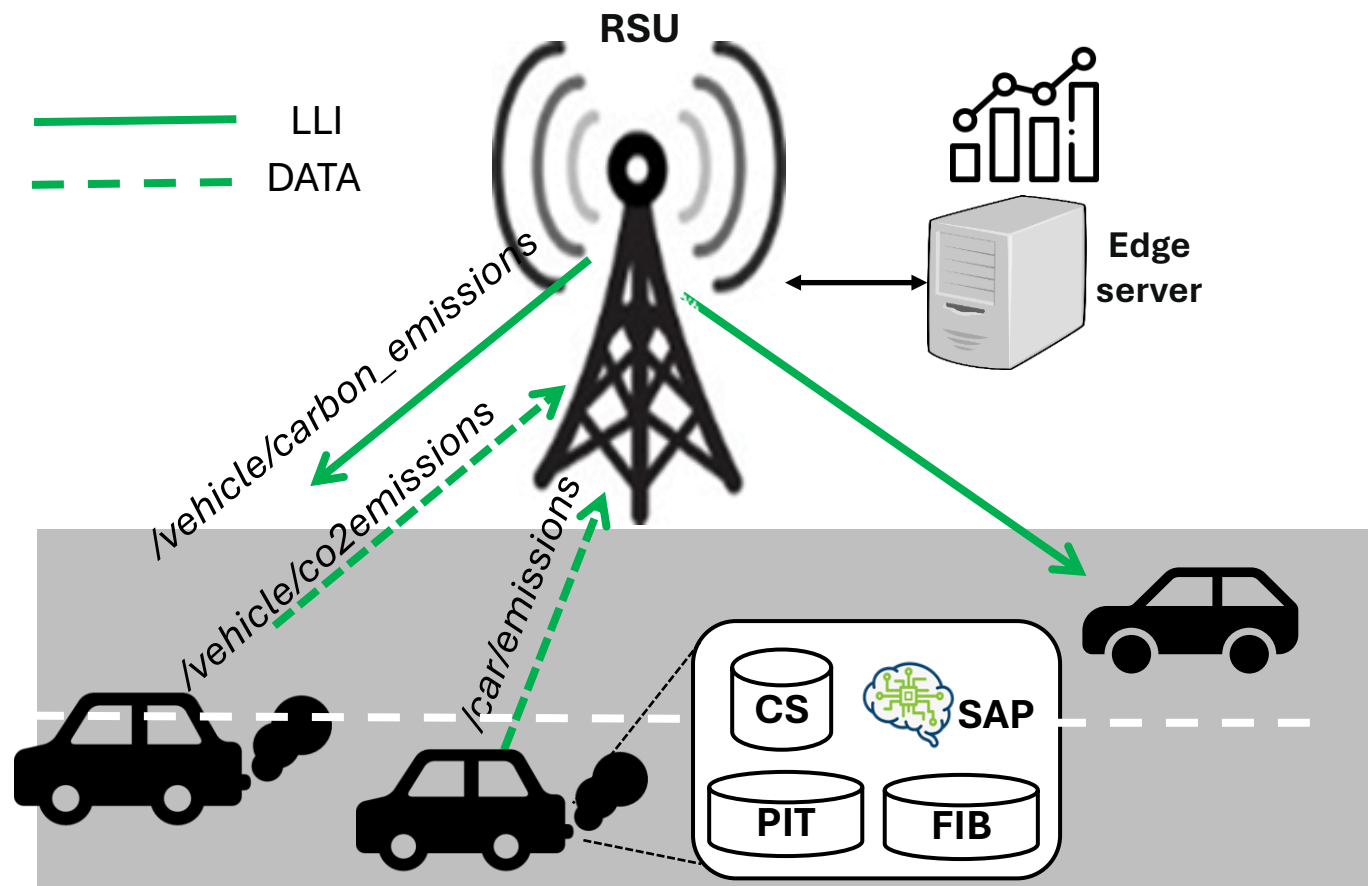
**INTEREST(/smartVehicle/speed/current)**



**DATA(/smartCar/speed/now{50km/h})**

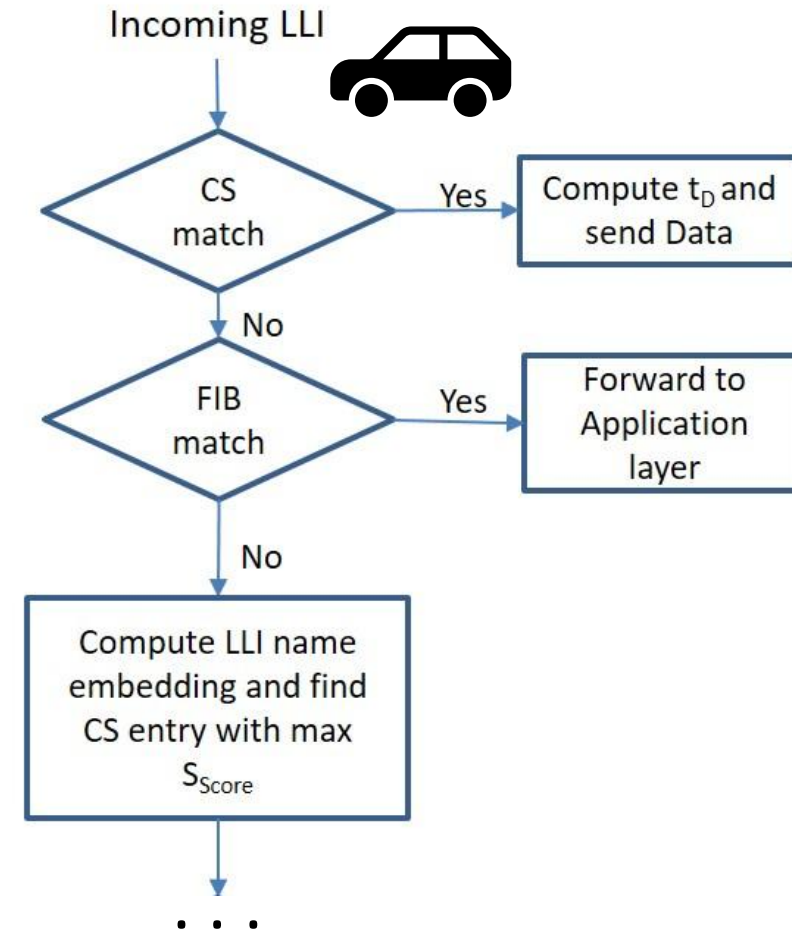
# The case of vehicular crowdsensing

- Long Lived Interests (LLIs) are broadcasted to collect data from vehicles acting as mobile producers
  - ✓ **Semantic Aware Processing (SAP)** is implemented!
- Single-hop interactions: LLI propagation beyond RSU coverage is not considered



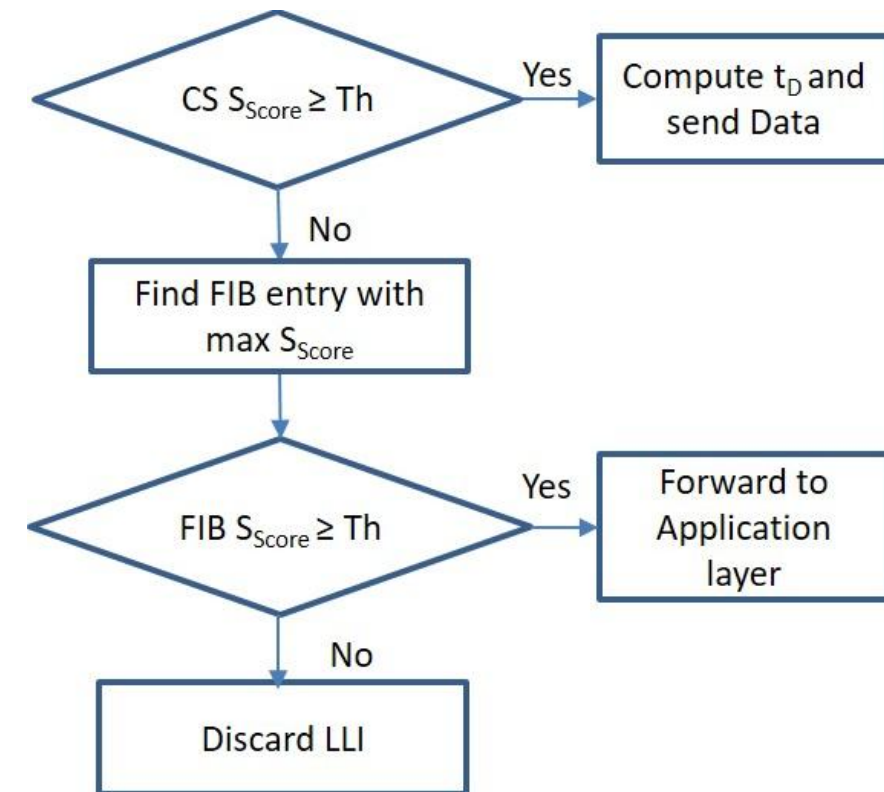
# The case of vehicular crowdsensing

- After receiving the LLI, the vehicle looks for an exact name match in the CS or the FIB
- Data is transmitted after a random defer time to avoid collisions
- If no exact match is found, SAP is triggered
  - ✓ Embedding of the LLI name is compared against the embeddings of Data names
  - ✓ A semantic score in  $[0;1]$  is computed using the cosine similarity metric



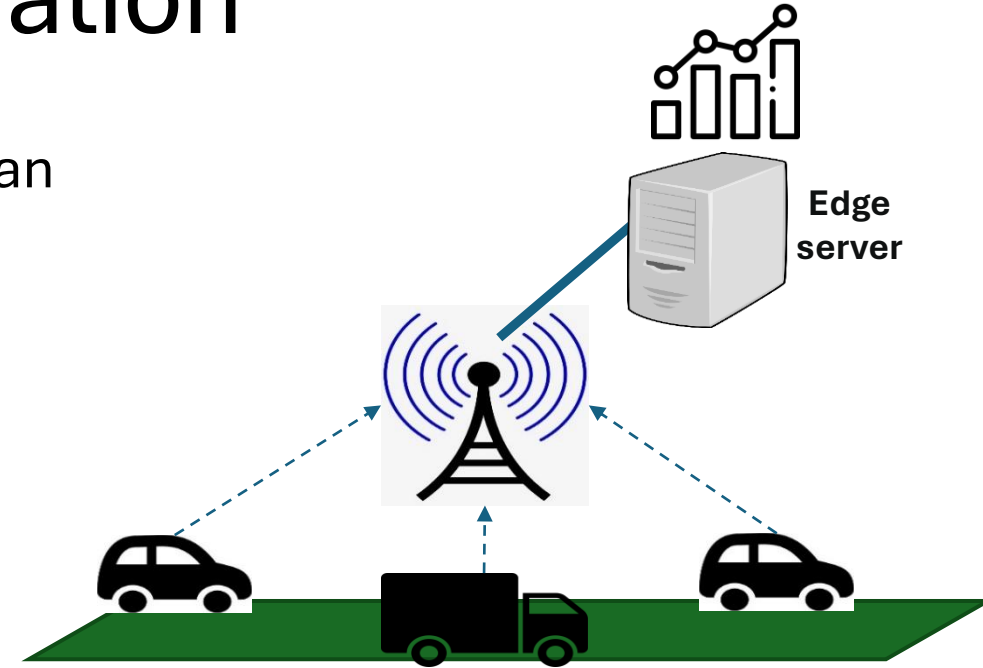
# The case of vehicular crowdsensing

- Data with the highest semantic score, that is also higher than a similarity threshold, is scheduled for transmission
- If no semantic match is found in the CS, similarity with FIB names is considered
- If also semantic FIB matching fails, LLI is discarded



# Semantic-aware NDN: Evaluation

- A crowdsensing service within the coverage area of an RSU
- A catalog of 500 LLI names
- Each vehicle can provide up to 100 contents
  - ✓ 5% exactly match LLI names
  - ✓ 95% have varying degree of similarity, including none
- SAP implemented with pre-trained Sentence Transformers models
  - ✓ All-mpnet-base-v2 (768-dimensional vector space)
  - ✓ All-miniLM-L12-v2 (348-dimensional vector space, 12 layers)
  - ✓ All-miniLM-L6-v2 (348-dimensional vector space, 6 layers)

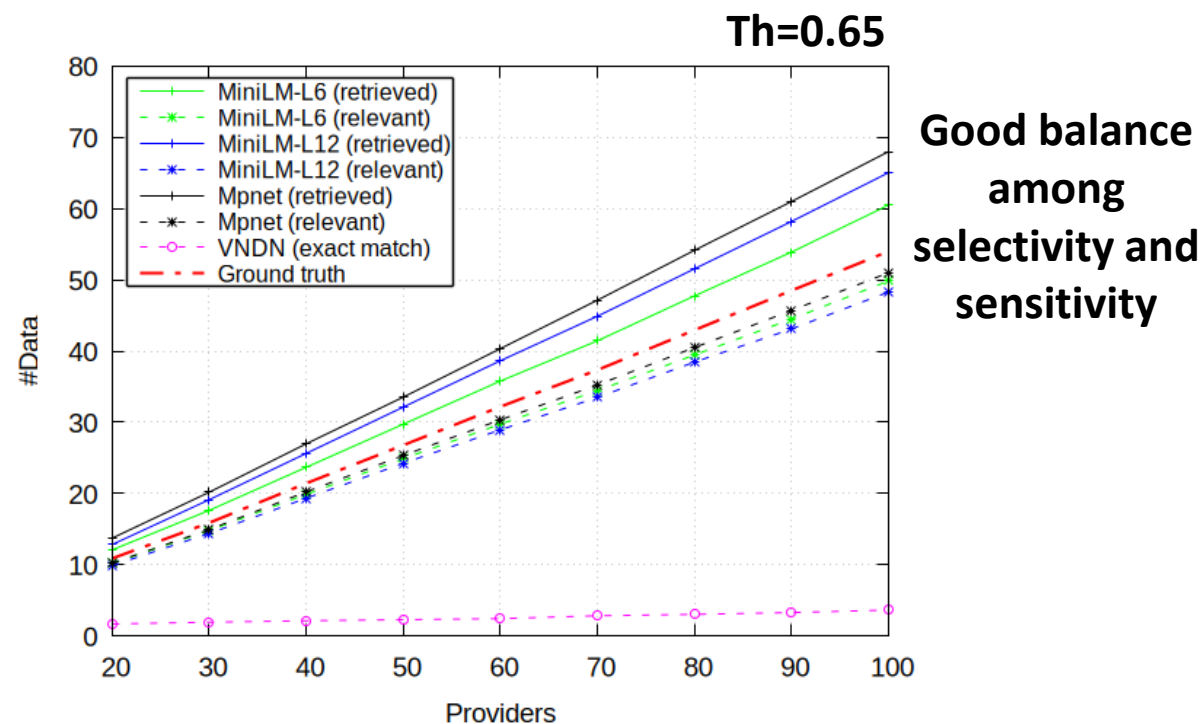
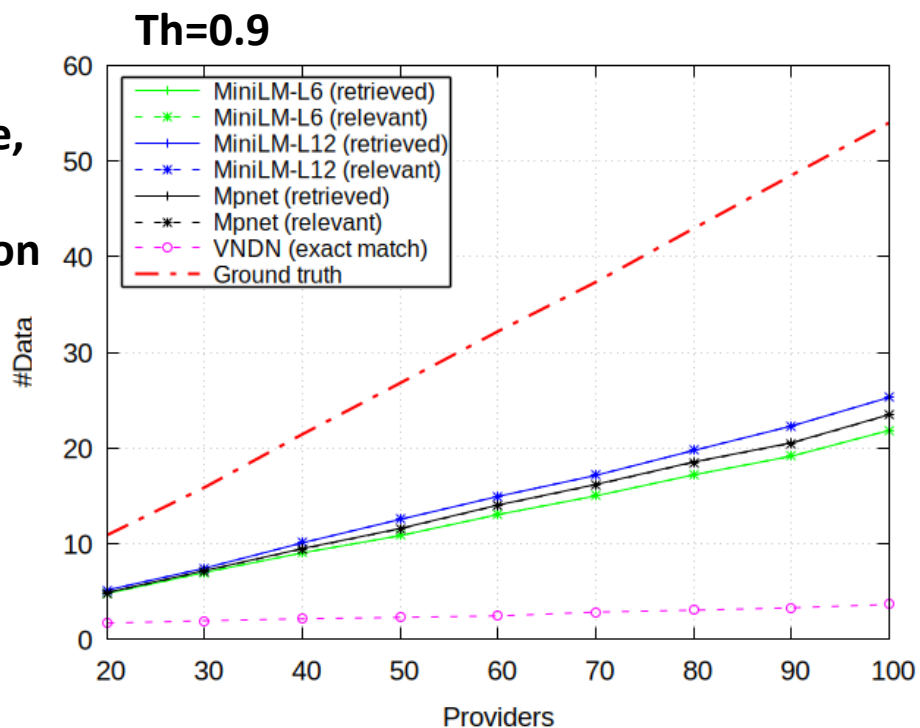


# Semantic-aware NDN: Evaluation

AVERAGE COMPUTATION TIME PER INTEREST NAME FOR DIFFERENT SENTENCE TRANSFORMER MODELS (IN SECONDS).

Model	Embedding Time	Matching Time	Total Time
Mpnet	0.0340	0.1601	0.1941
MiniLM-L12	0.0131	0.0419	0.055
MiniLM-L6	0.0095	0.0256	0.0351

Too restrictive,  
resulting in  
under-collection



Good balance  
among  
selectivity and  
sensitivity

# Conclusions

- **NDN for AI**

- NDN is a natural communication substrate for distributed AI at the edge: its core features (named data, in-network caching, stateful forwarding) directly address networking bottlenecks
- Early results confirm gains over TCP/IP under realistic lossy wireless conditions for FL and split inference applications

- **AI for NDN**

- Semantic intelligence embedded in the NDN forwarding fabric overcomes the fundamental naming heterogeneity problem in open, dynamic environments
- Early results showed flexible data discovery in vehicular crowdsensing without any prior naming agreement

# Future works

- **NDN for AI**

- Naming schemes for AI artifacts: versioning, model lineage, and parameter provenance
- Adaptive forwarding strategies for split inference: how should the NDN FIB/PIT be updated dynamically as the splitting strategy changes across nodes?
- Caching of inference outputs or model updates

- **AI for NDN**

- Strategies for ground-truth validation in real scenario
- Multi-hop forwarding with semantic awareness
- Semantic-based caching

# Main references

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# Thank you!

**Any questions?**

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