An Architecture for Task and Traffic Offloading in Edge Computing via Deep Learning

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How many times have you delegated a task?

WHO CAN HELP ME?

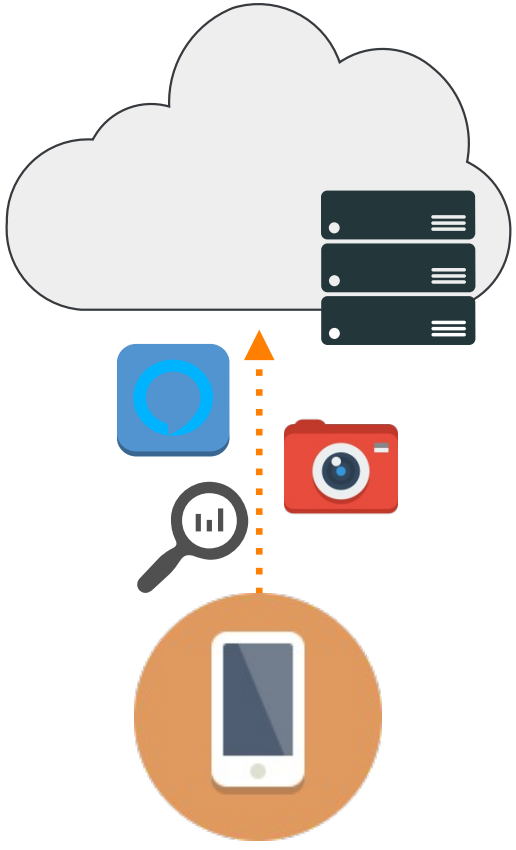
WHO IS FASTER?

What is task offloading?

Task offloading is the process of transferring tasks to another platform.

It is often adopted in the context of Mobile Edge Computing (MEC).

The goal is to reduce power consumption and get results faster.



How should tasks be offloaded?

There is no architecture describing the offloading mechanisms.

Currently used routing strategies, such as OSPF, are performance unaware.

OSPF computes the shortest path to a destination, without considering any performance indicator, which can be crucial in critical scenarios.

What tools do we have?

Recently Software-Defined Networking (SDN) has spreaded, with the idea of separating data and control plane.

Knowledge-Defined Networking (KDN) is the idea of building a knowledge plane (1) for the network and manage it accordingly.

The combination of SDN & KDN is a powerful tool for network management.

[1] D. Clark, C. Partridge, J. Ramming, and J. Wroclawski.
A knowledge plane for the internet.
In Proc. of SIGCOMM '03. ACM, New York, NY, USA, 3-10.

What can we do?

- Architecture definition to address the complexity problem
- Knowledge Plane to support network management
- Performance aware traffic steering

Talk overview

- Offloading Architecture
- Results
- Limitations

Talk overview

- Offloading Architecture
  - Architecture
  - Task Offloading Protocol
  - Path Prediction via Deep Learning
- Results
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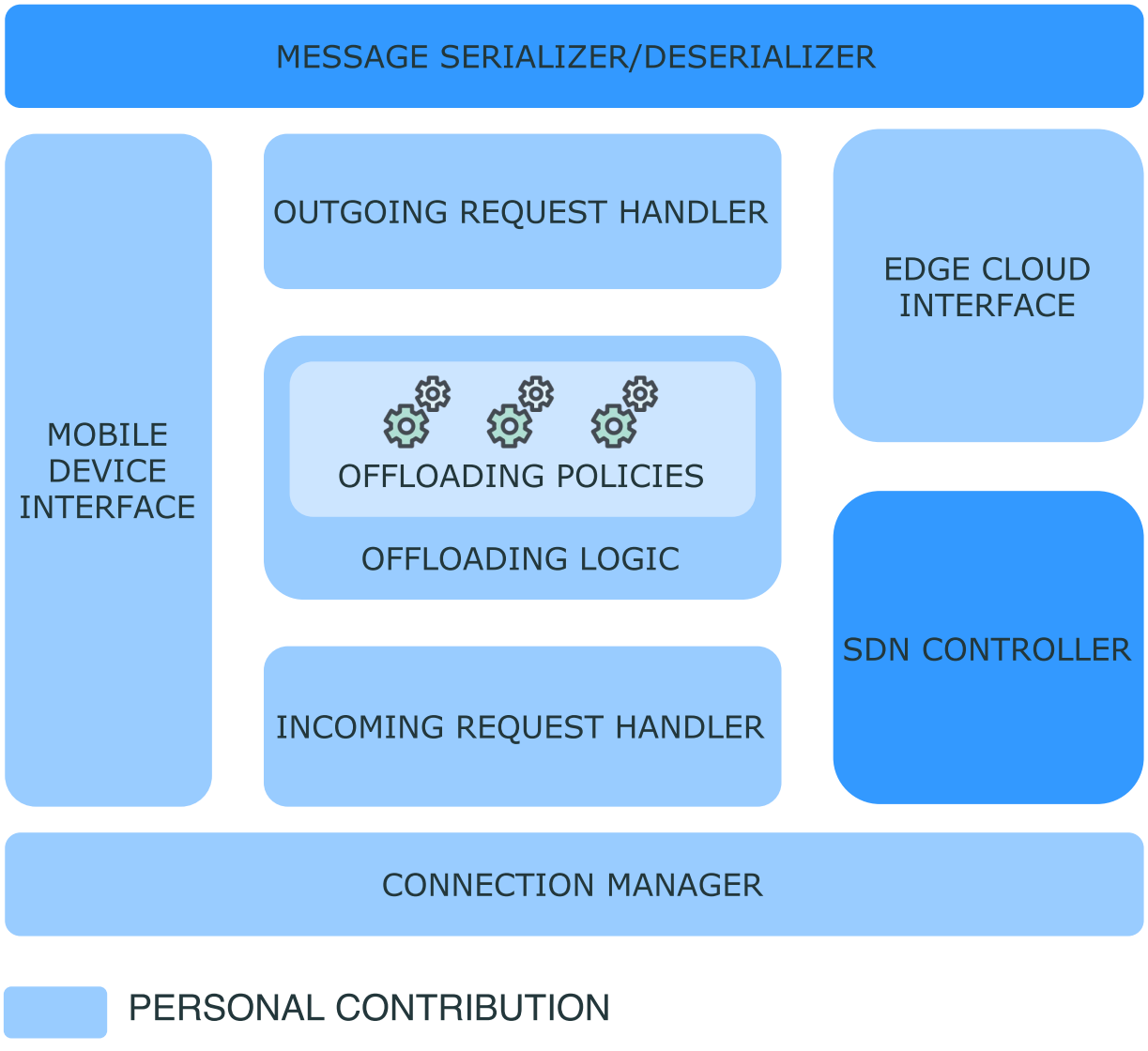
What is an architecture?

In Computer Science and Engineering, an architecture describes the necessary and sufficient set of invariances to achieve a goal.

The architecture is also responsible of separating the different functionalities by identifying who does what.

Our contribution: offloading architecture



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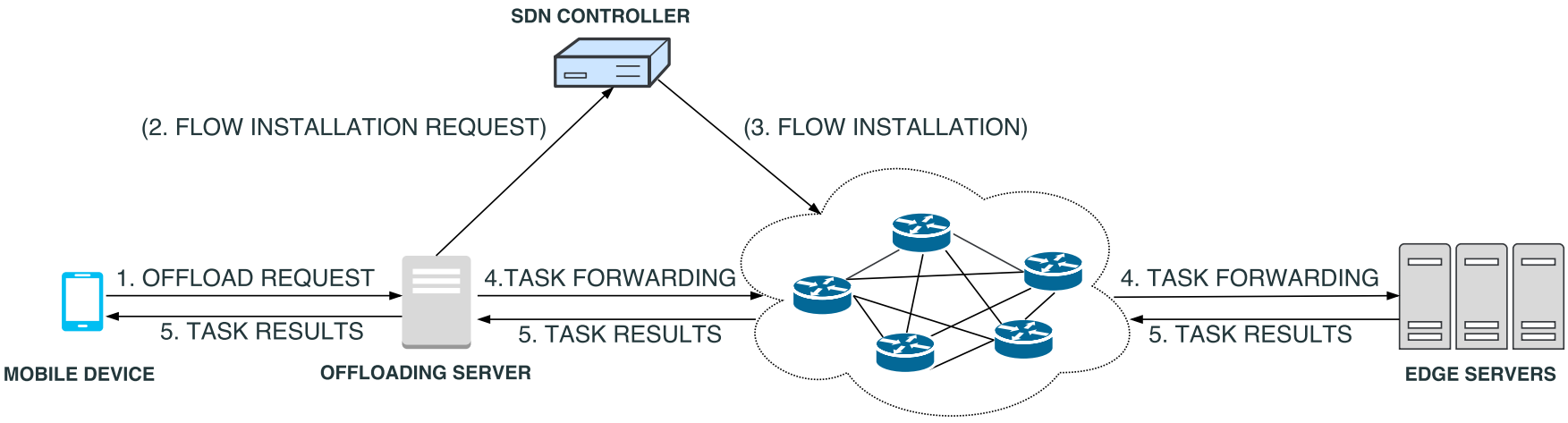
Our contribution: task offloading protocol



The protocol allows the client to specify:

- task requirements such as CPU, memory and latency
- offloading logic (e.g. nearest server)

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    - Overview
    - Dataset
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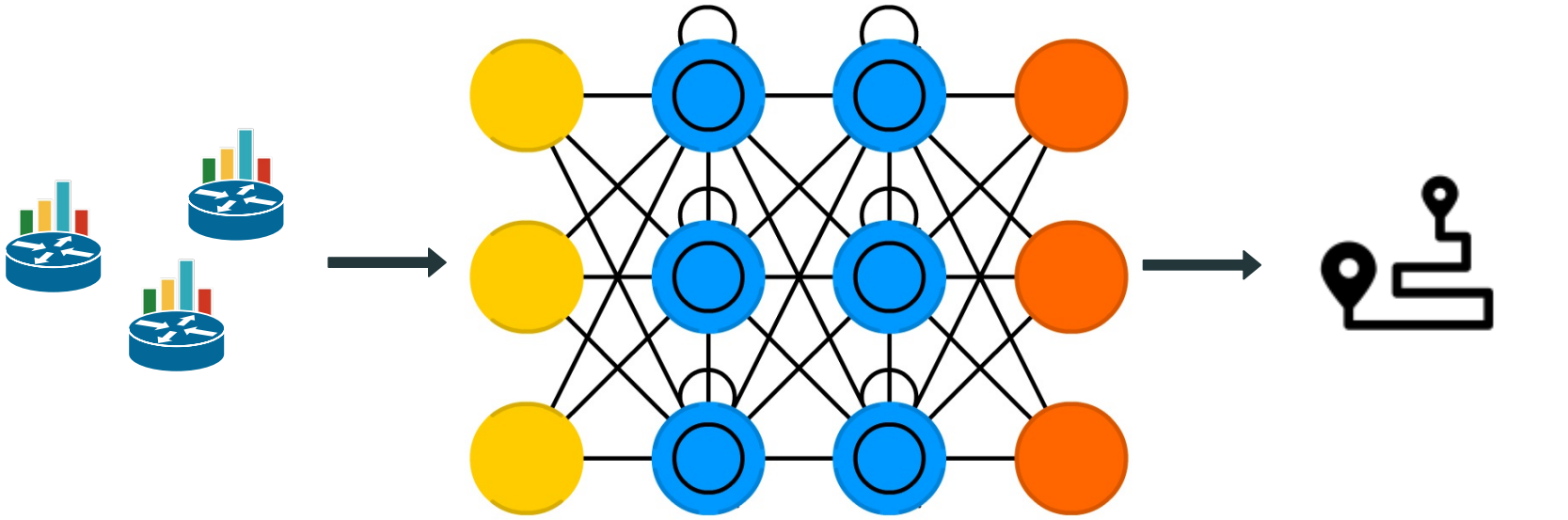
Our contribution: path prediction via deep learning

Machine learning is a powerful tool for inference tasks

IDEA: Routing problem as inference problem

How to determine the best path?

Use traffic pattern as performance indicator.
Perform path prediction with machine learning.



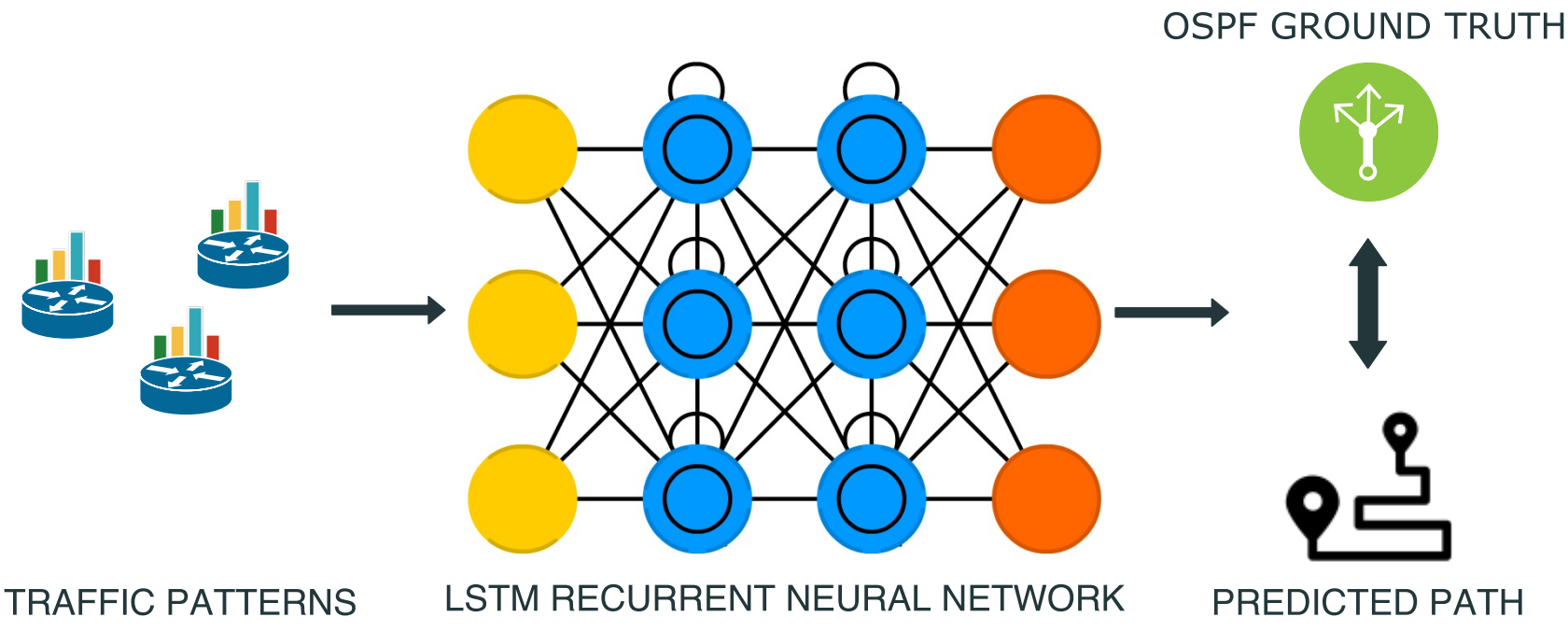
Long Short-Term Memory (LSTM)

LSTM is an evolution of recurrent neural networks (RNNs) capable of memorizing data temporal patterns

Objective:
Learn how traffic patterns evolve and route accordingly

Learning from who?

LSTM RNNs are a supervised learning method, they require data to learn from.
We use OSPF routing decisions as a ground truth.



Our prediction model

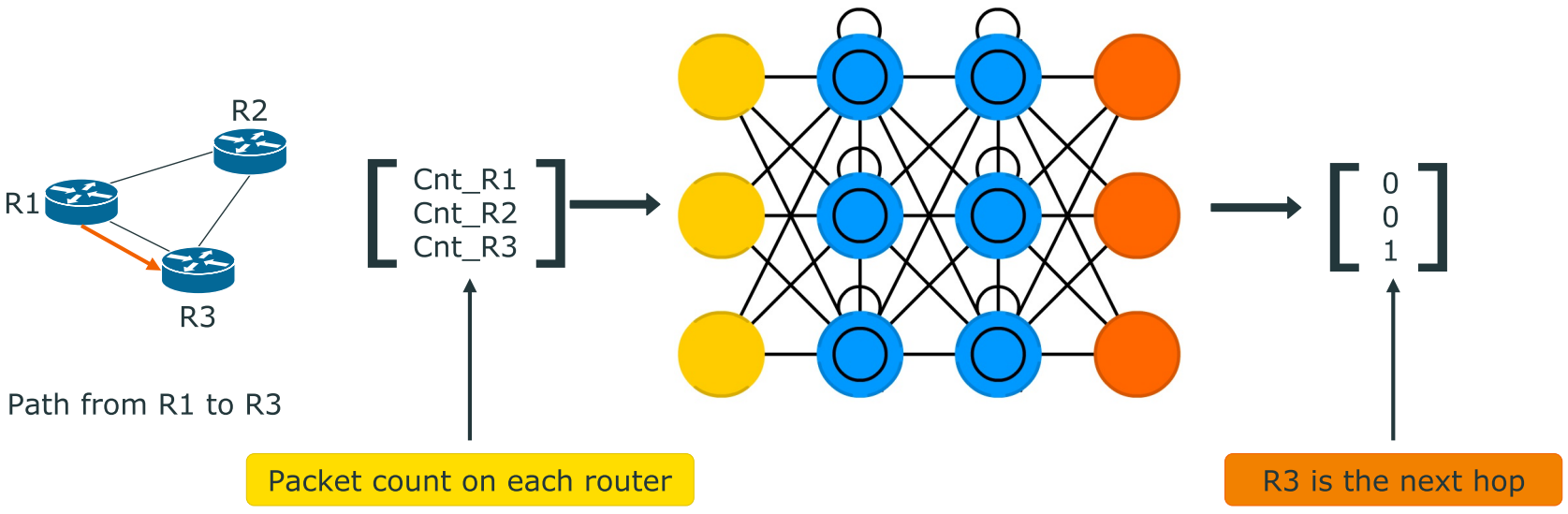
To use a LSTM we must define the model input and output.

Input:

Incoming packets count on each router

Output:

One-hot encoded vector with the next hop in the path



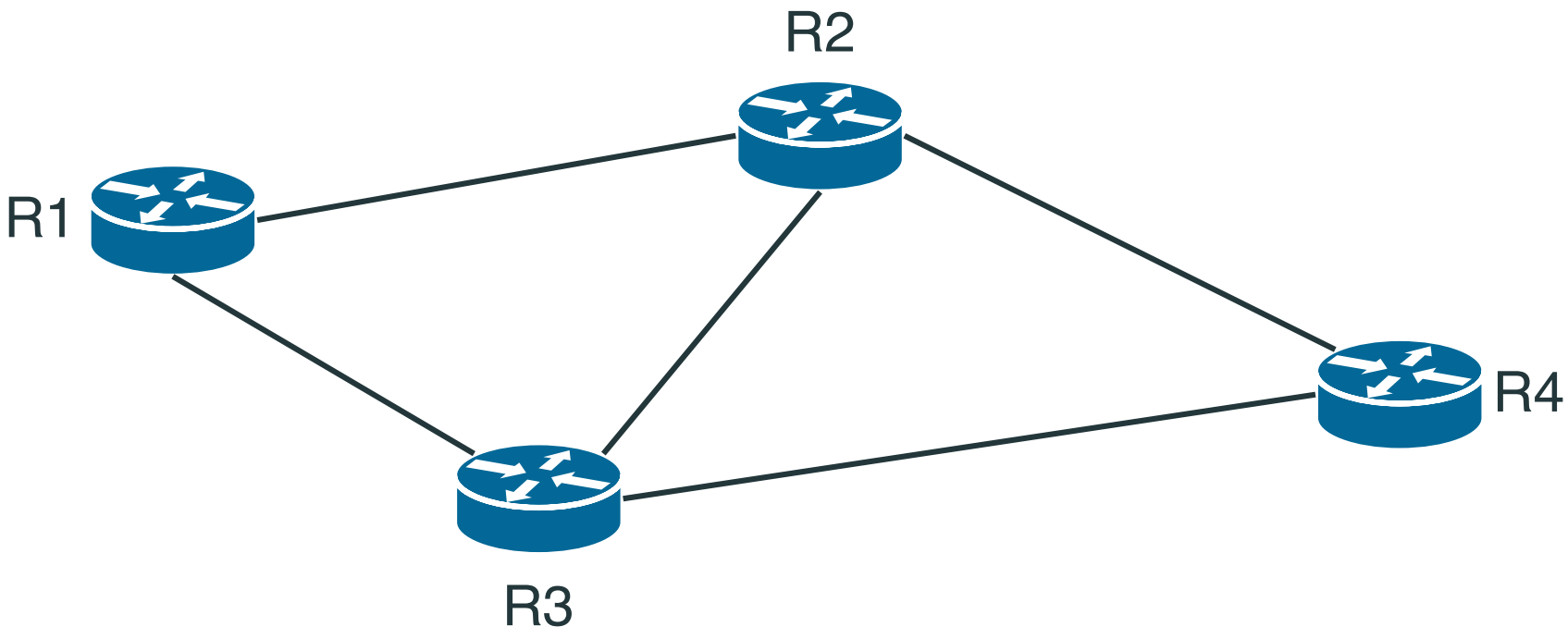
Path prediction process

Training a single model for all the targets in the topology is not feasible.

SOLUTION: train a model for all the source-destination pairs in the network.

To compute the whole path we iteratively use the model of the predicted next hop until the destination is reached.

Example: computing the path from R1 to R4



Step 1 - model = R1-R4 –> next hop = R2

Step 2 - model = R2-R4 –> next hop = R3

Step 3 - model = R3-R4 –> next hop = R4

Computed path: R1 - R2 - R3 - R4

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Dataset generation

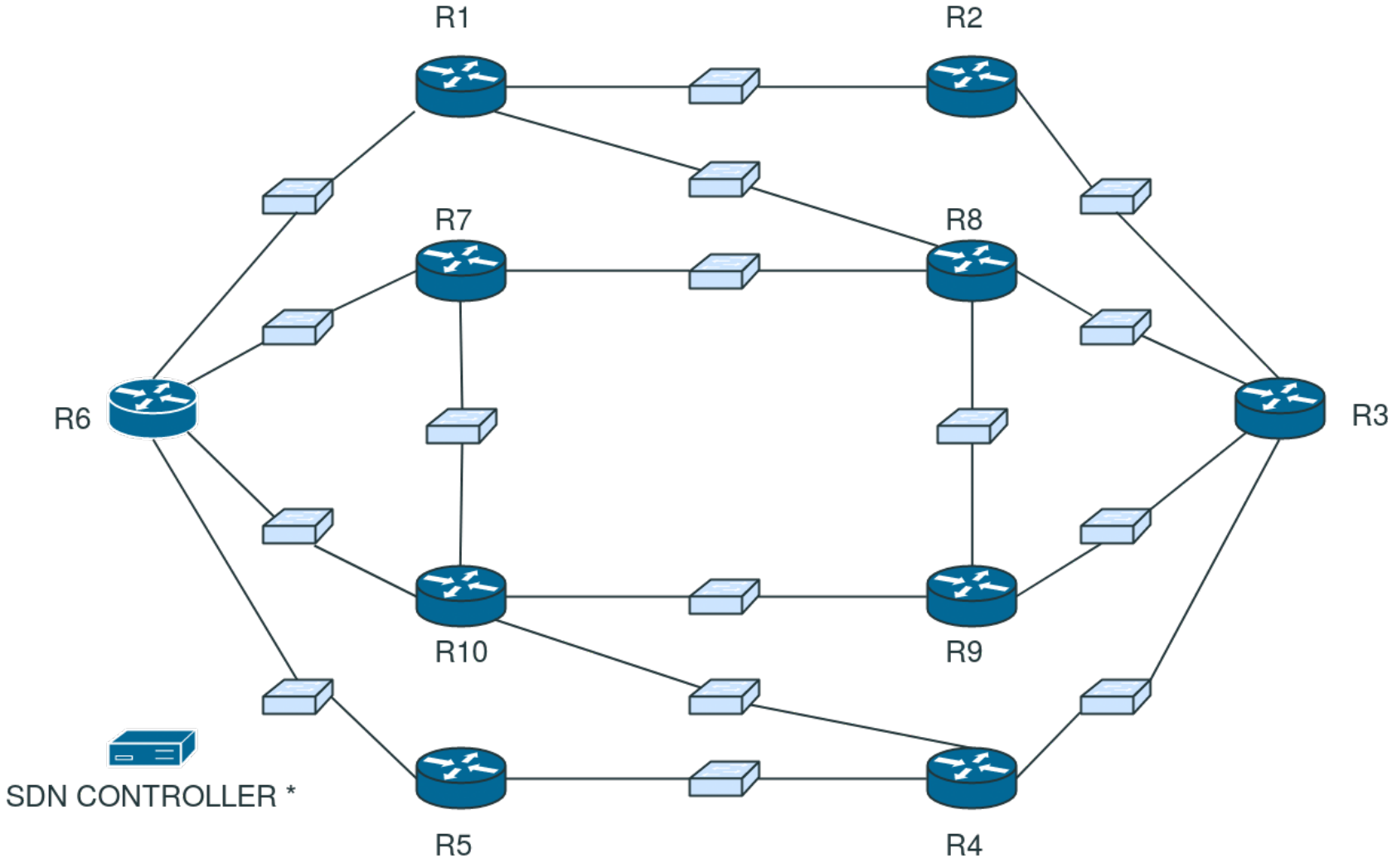
To train our model we need:

- network topology
- routing algorithm
- packet counter

We could not find any public dataset suited to our needs so we create our own.

Network topology

We create this topology using MiniNeXt



** All switches are connected to the SDN controller*

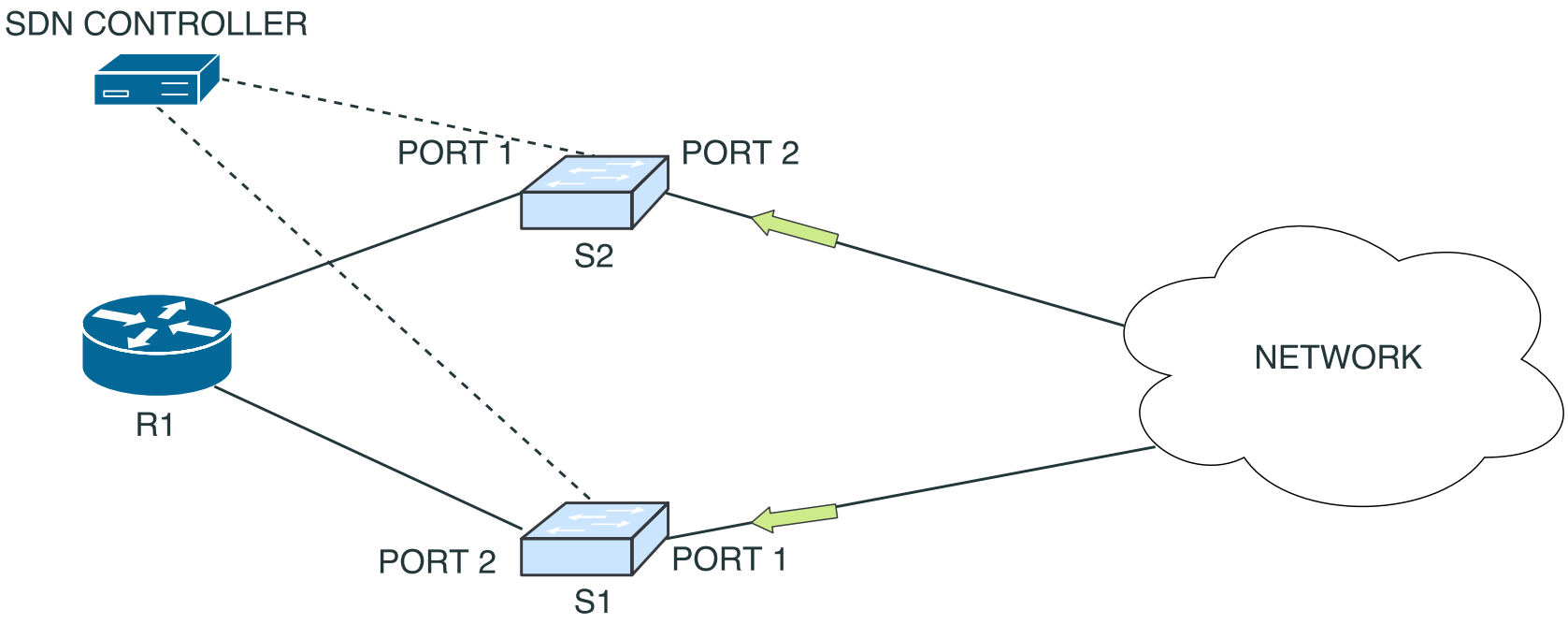
Routing algorithm

To run routing algorithms on MiniNeXt nodes we use Quagga. Quagga is a routing suite providing different routing algorithms (e.g OSPF, IS-IS, RIP).

We choose Open Shortest Path First (OSPF) because of its wide adoption as iBGP.

Packet counter

The SDN controller –Ryu– is responsible of retrieving the packet count.



Dataset generation steps

For an arbitrary number of times:

1. Initialize the topology with different link speed
2. Simulate traffic between routers
3. Save packet count and routing tables
4. Stop the traffic simulation and tear down the network
5. Back to step 1

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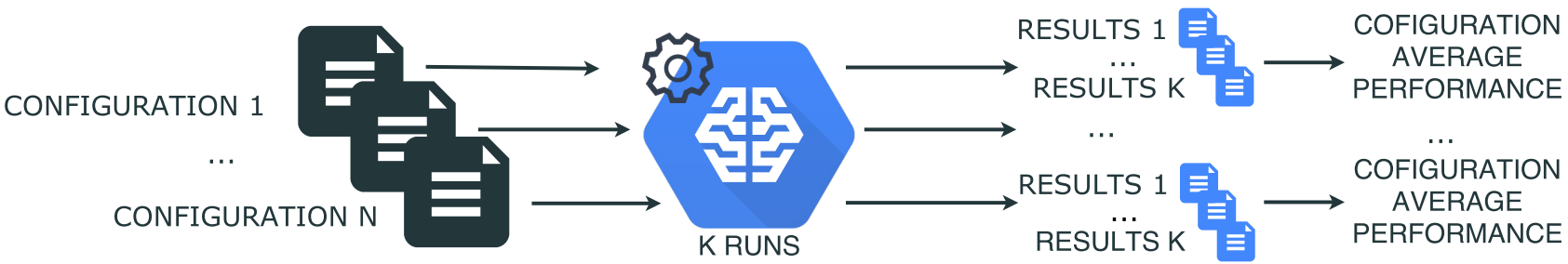
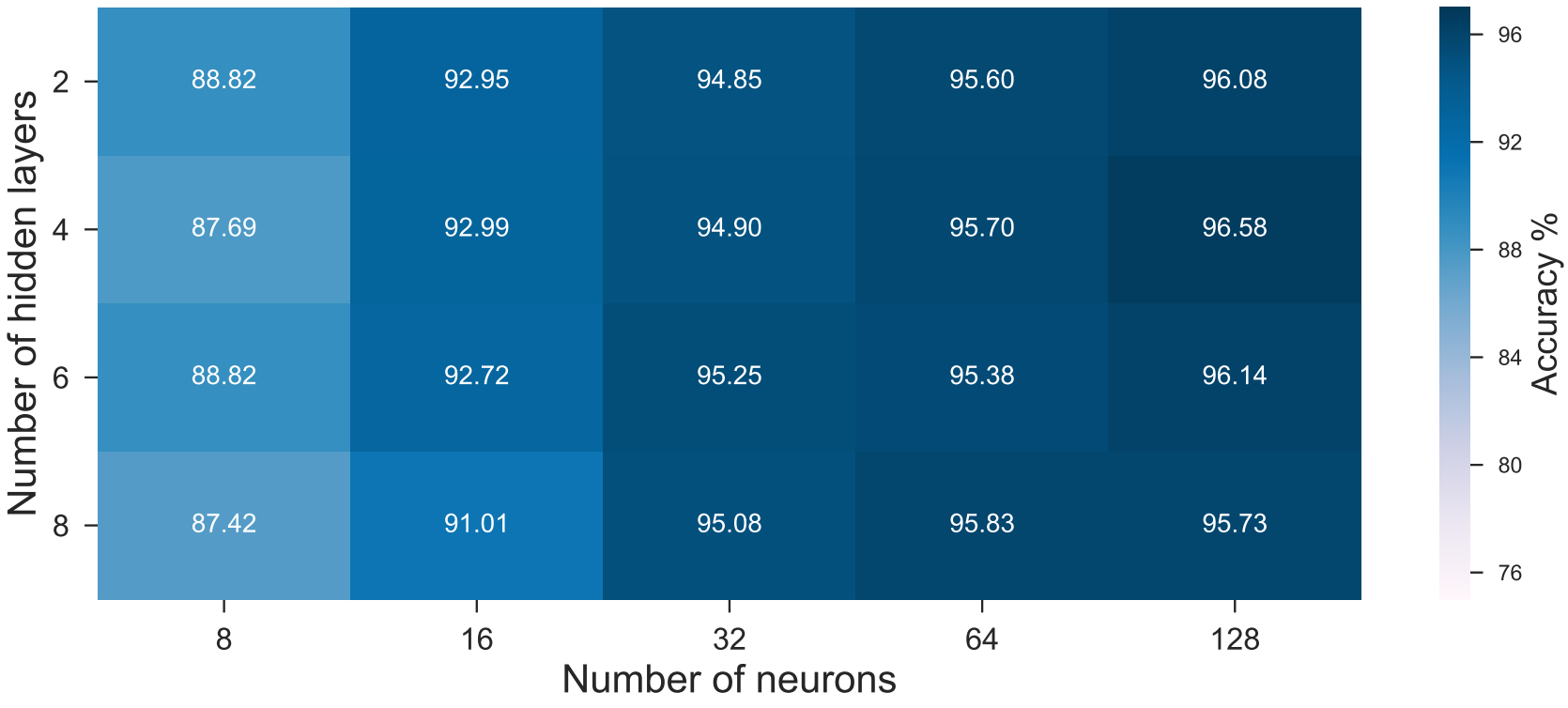
How to decide the LSTM structure?

The number of layers and neurons cannot be decided a priori. Cross validation is a powerful technique to determine the model parameters.

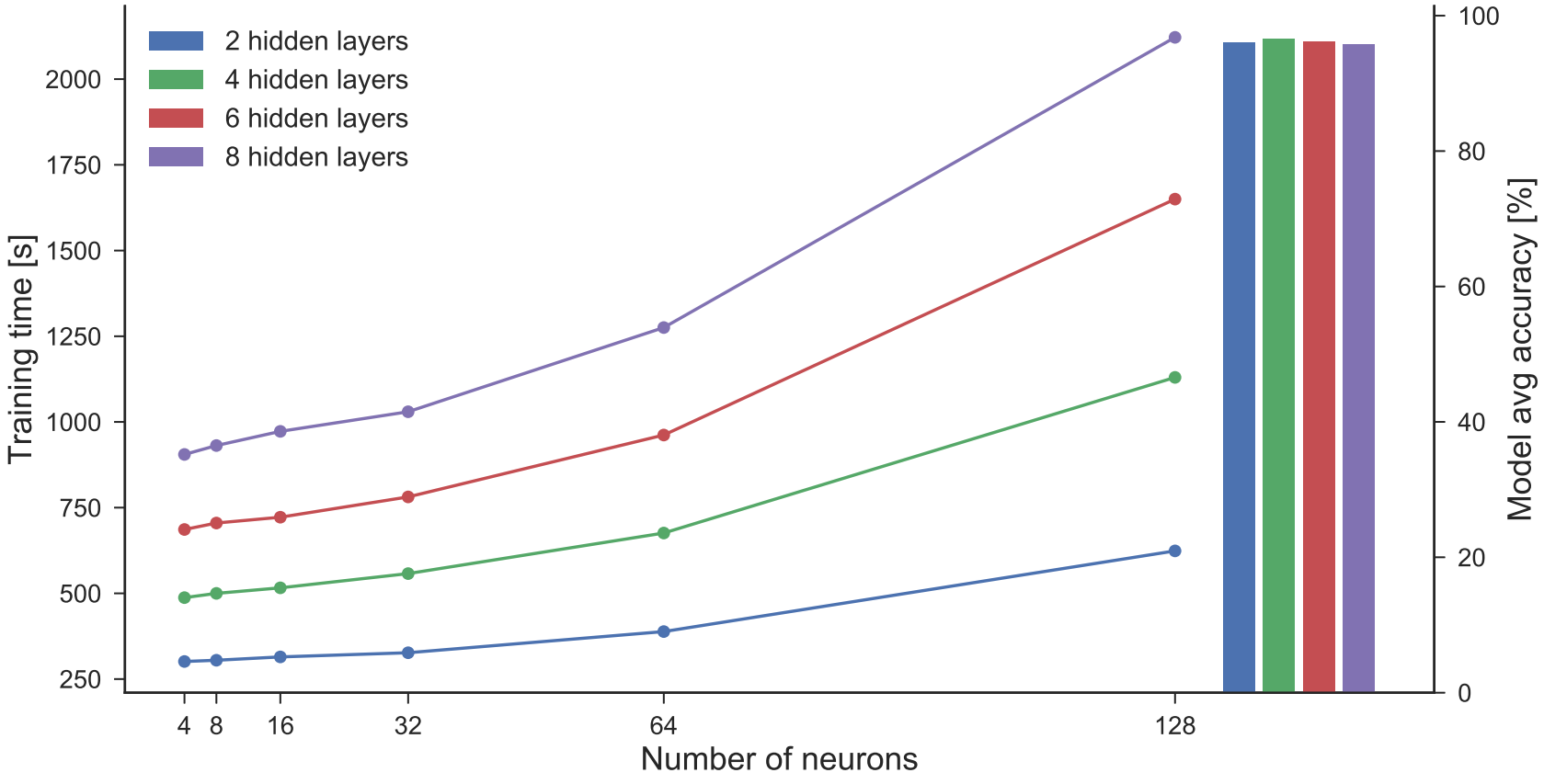


Accuracy: more neurons or more layers?

Neurons affect performance more than hidden layers

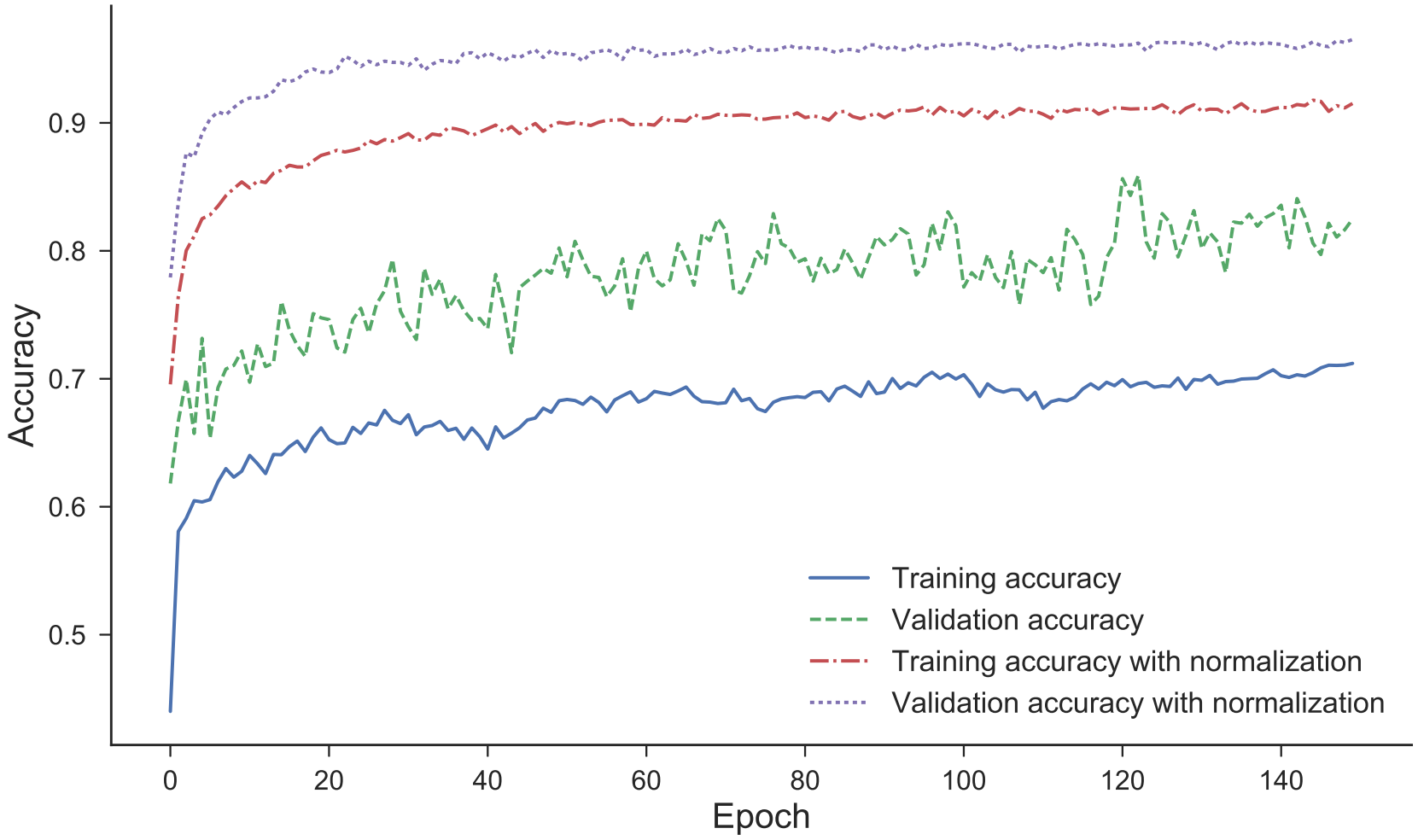


Finding the trade-off: training time



** Accuracy shown only for models with 128 neurons*

Tuning the network: input normalization



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The system is able to emulate OSPF

We test the system's ability to behave like OSPF by averaging the performance of all the models on the test set.

The LSTM achieves an average accuracy of **98.71%** with respect to OSPF.

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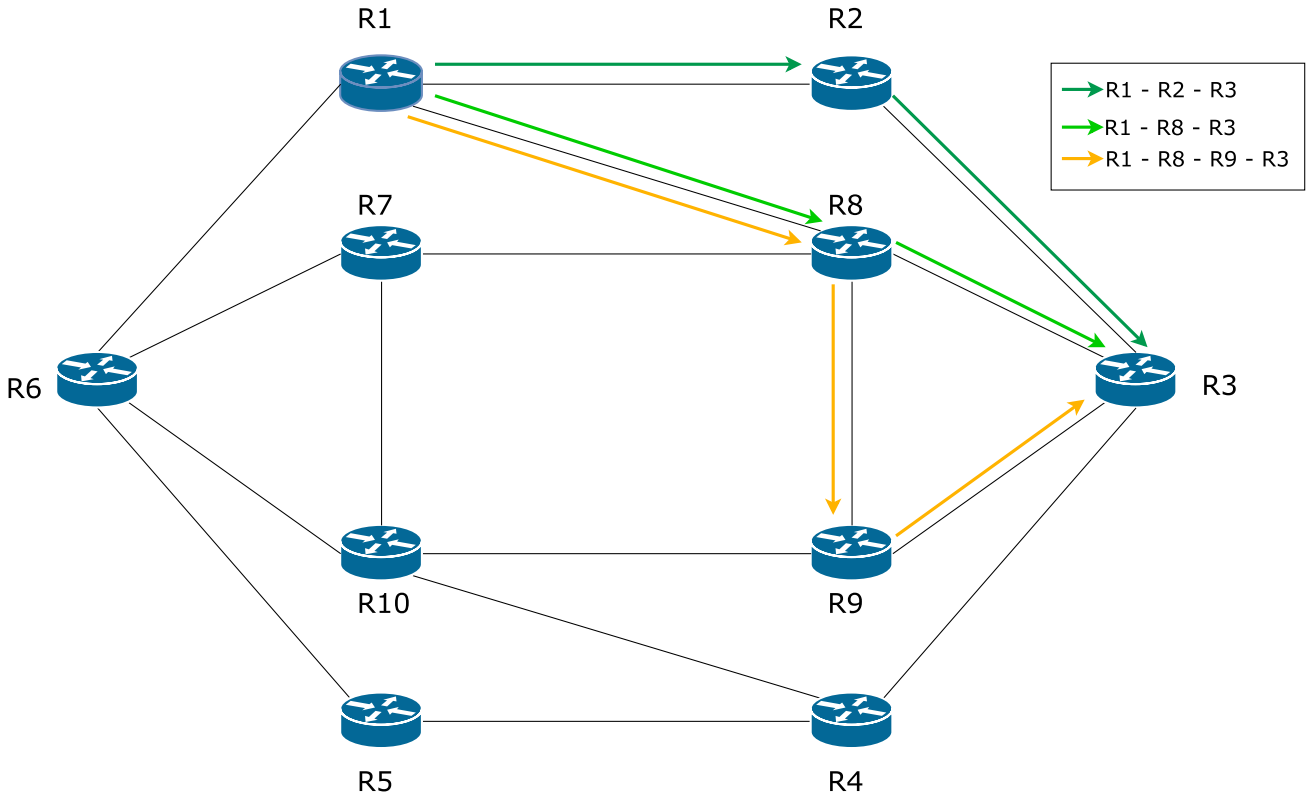
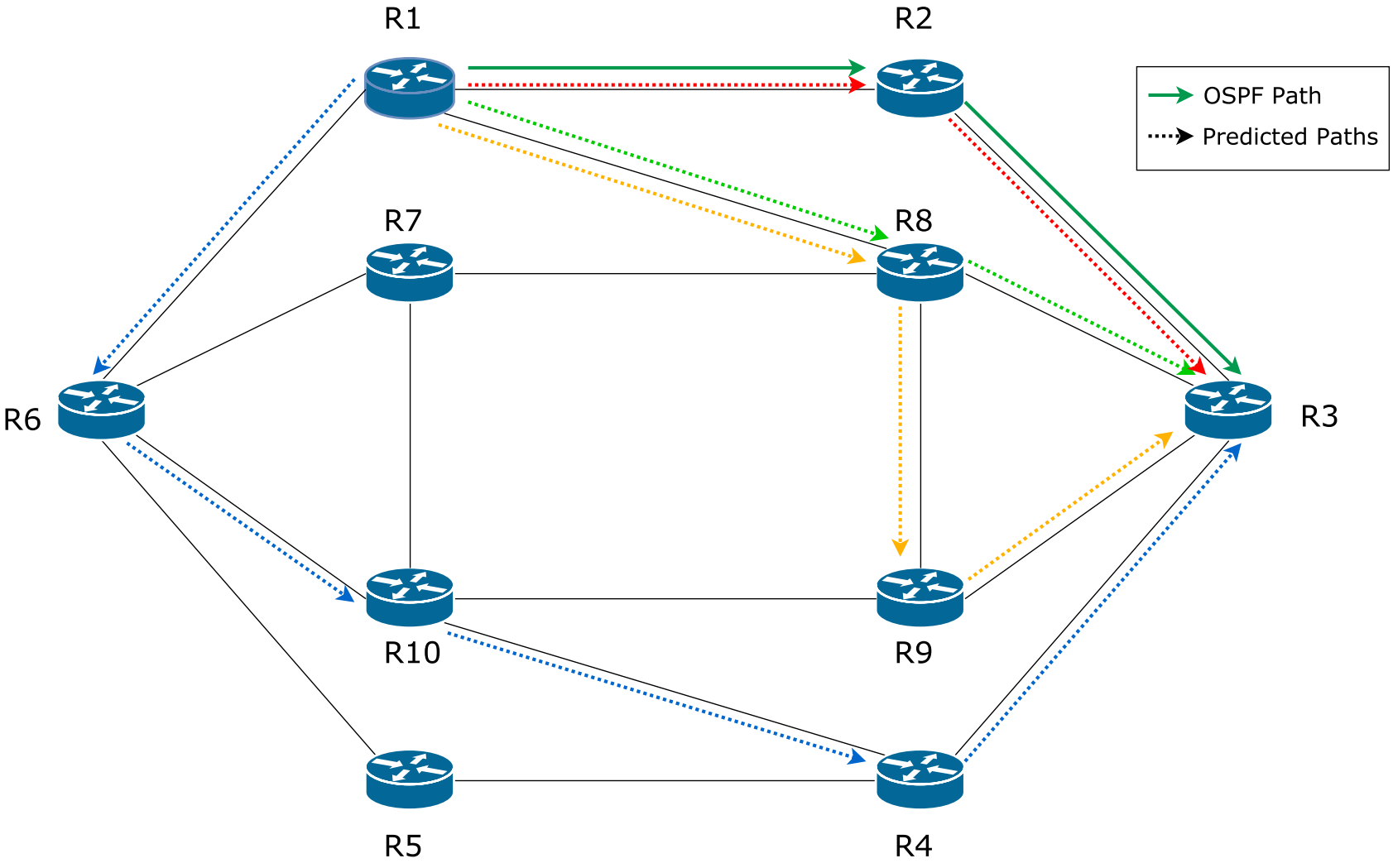
Is the system performance aware?

We select a target and analyze, through an example, how our system behaves differently from OSPF in case of link loss.



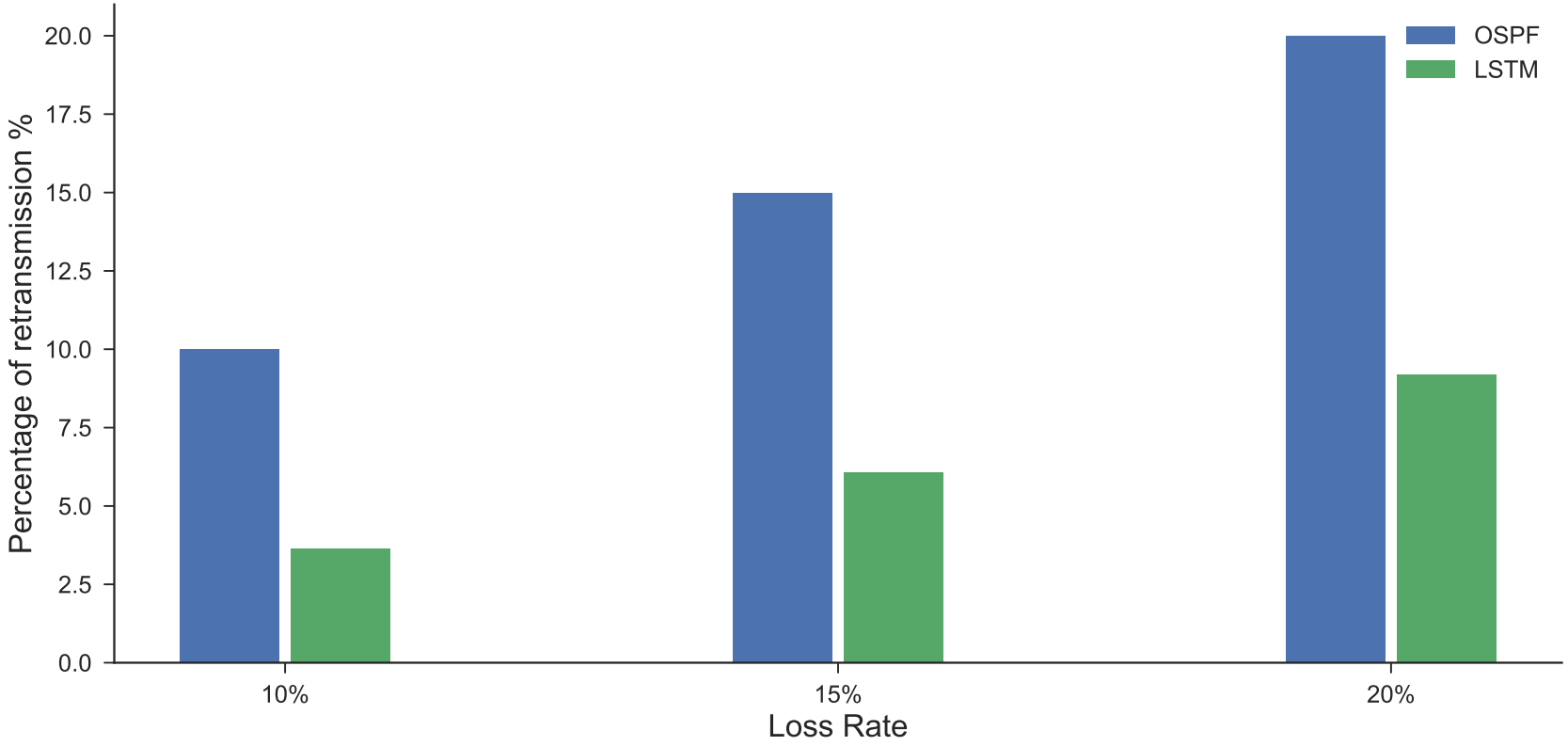
The system exhibits a dynamic behavior

The LSTM path predictor is able to suggest multiple paths



LSTMs outrun current approaches in terms of retransmission

In case of malfunctioning links, our system has a lower retransmission percentage then traditional routing



OSPF = Open Shortest-Path First, LSTM = Long Short-Term Memory

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Limitations

Testbed:

- The functionalities of Mininet are limited
- Higher link loss decreases the prediction efficiency

Computation:

- The number of models to train is big
- The trained models occupy GBs of memory

Future work

Current results are encouraging, therefore we want to further investigate the problem by:

- getting rid of Mininet emulation environment constraints
- testing the method on larger networks (e.g GENI)
- running the testbed on a more scalable platform (e.g GPU)
- exploring more machine learning techniques (e.g reinforcement learning)

Take home messages

- Mobile edge computing is a complex problem

Take home messages

- Mobile edge computing is a complex problem
- We prototyped an architecture for MEC offloading orchestration

Take home messages

- Mobile edge computing is a complex problem
- We prototyped an architecture for MEC offloading orchestration
- We developed a machine learning-based, performance aware routing strategy that improves on classic iBGP mechanisms

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Thank you for the attention

Alessandro Gaballo

Protocol 1

```
message OffloadRequest {
    message Requirements {
        enum Latency {
            URGENT = 0;
            STANDARD = 1;
            LOOSE = 2;
        }

        float cpu = 1;
        int32 memory = 2;
        Latency latency = 3;
    }
```

Protocol 2

```
enum Type {
    LAMBDA = 0;
    STANDARD = 1;
}

message Task {
    message TaskWrapper {
        enum WrapperType {
            JAR = 0;
            EGG = 1;
        }
```

Protocol 3

```
            string name = 1;
            WrapperType type = 2;
            bytes task = 3;
        }

        oneof task_location {
            string task_id = 1;
            TaskWrapper wrapper = 2;
        }
    }
```

Protocol 4

```
    Requirements requirements = 1;
    Type type = 2;
    Task task = 3;

}

message Response{
    enum Result {
        OK = 0;
        INVALID_MSG_SIZE = 1;
        INVALID_REQUEST = 2;
    }
```

Protocol 5

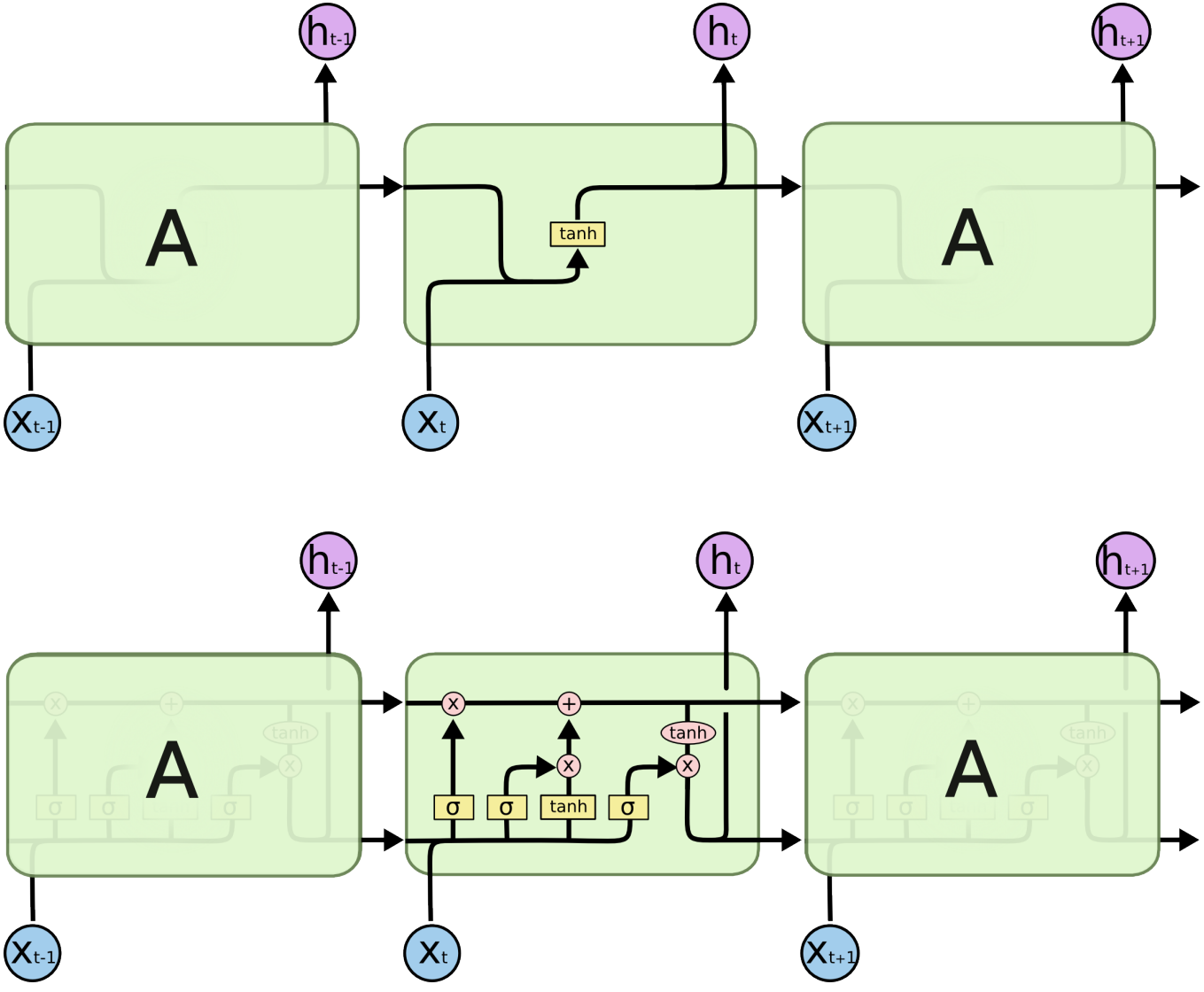
```
    Result result = 1;
    string msg = 2;
}

message Message{
    enum Type {
        OFFLOAD_REQUEST = 0;
        RESPONSE = 1;
        TASK = 2;
    }
```

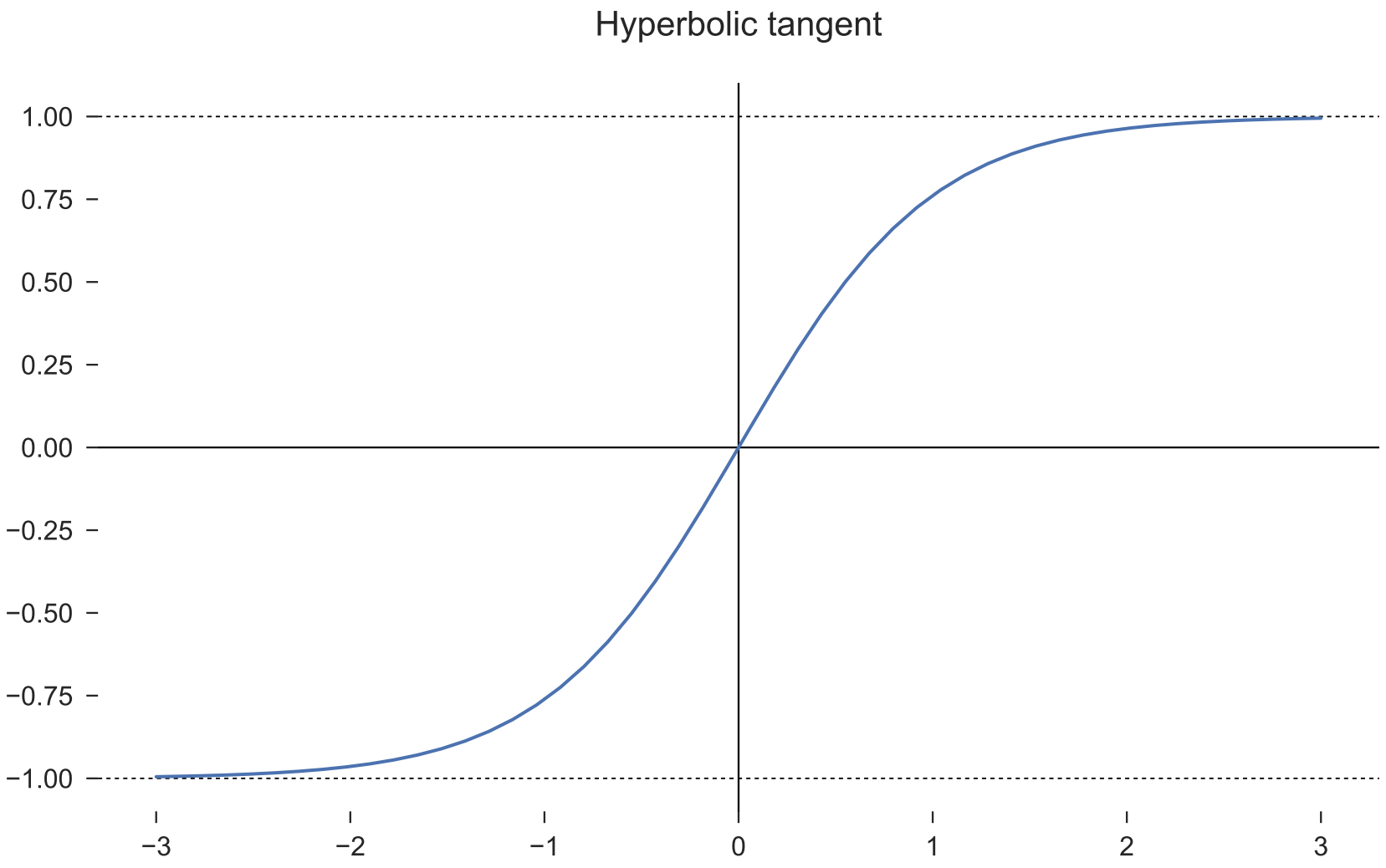
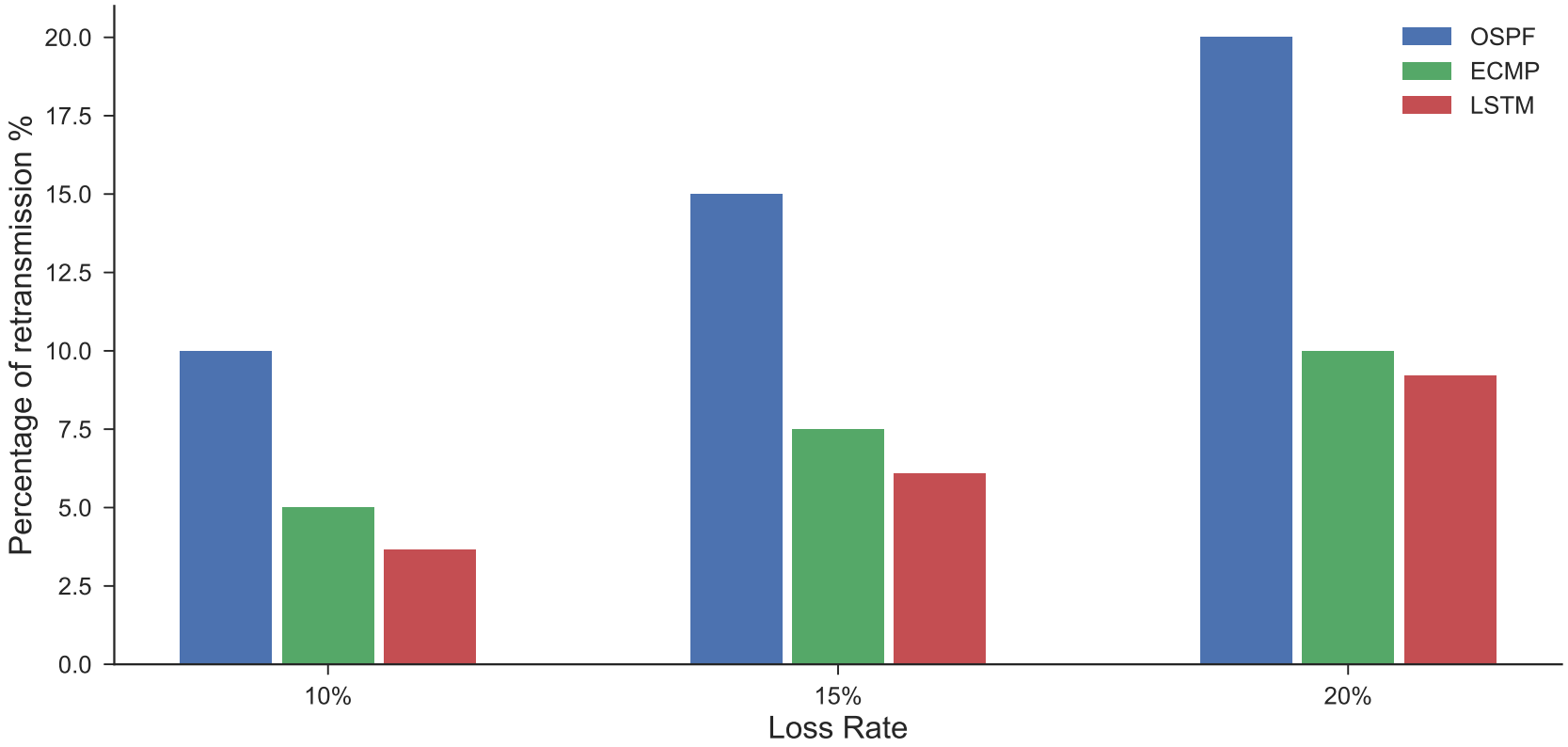
Protocol 6

```
    Type type = 1;
    oneof msg_type {
        OffloadRequest off_req = 2;
        OffloadRequest.Task task = 3;
        Response response = 4;
    }
}
```

Recurrent Neural Network vs Long Short Term Memory



LSTM cells - activation function



Comparing with other techniques