# Advancing Packet-Level Traffic Predictions with Transformers

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- Limited scope: Models fail outside original training environment
- Resource intensive: Always re-doing training from scratch

# Why use Transformers?



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- Efficient learning with attention mechanism
- Generalizing using large datasets available
- State-of-art for sequence learning problems
- Network packet data is a sequence

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- Question answering
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#### BERT: Generalizing to many tasks in NLP

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Vision Transformer: Generalizing to many tasks in CV

- Image classification
- Object detection
- Image segmentation

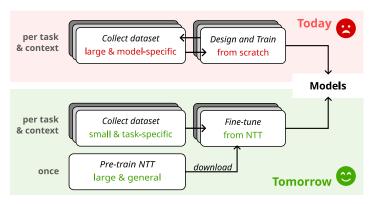


# Our Transformer prototype

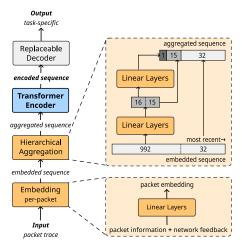
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Pre-train today, fine-tune and re-use tomorrow



The Network Traffic Transformer (NTT) with an embedding layer, an aggregation layer, a transformer encoder and a task-specific replaceable decoder.

Feature selection for initial NTT's input data:



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- Relative timestamp: To learn sequence order
- End-to-end delay: To learn network state information
- Packet size: To learn packet state information

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- Learn network dynamics: Reconstruct masked delay values
- Scale to large sequences: Aggregate inputs (> 1000s of values)

# Ensuring varied dynamics in our pre-training datasets



Initial topology for data generation

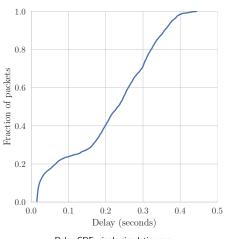
### Ensuring varied dynamics in our pre-training datasets

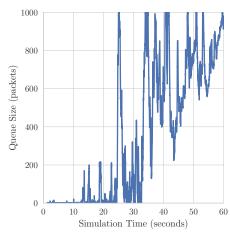


Initial topology for data generation

- Varied start times across sender application flows
- Enough variance in pre-training data dynamics

### Ensuring varied dynamics in our pre-training datasets



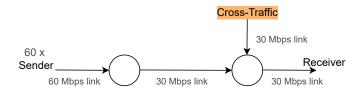


Delay CDF, single simulation run

Bottleneck queue profile on the single-path topology

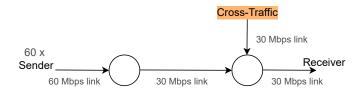
Distribution plots on pre-training data

# Our NTT allows for generalization on network dynamics



Fine-tuning data generation, single path topology

### Our NTT allows for generalization on network dynamics



Fine-tuning data generation, single path topology

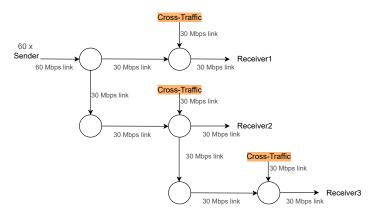
- Two bottleneck dynamics to learn
- Packet-level fine-tuning task: Predict last delay
- Flow-level fine-tuning task : Predict Message Completion Time (MCT)

### Our NTT allows for generalization on network dynamics

all values $\times 10^{-3}$	Pre-training	Fine-tuning	
	Delay	Delay	log (MCT)
NTT			
Pre-trained	0.072	0.097	65
From scratch	-	0.313	117
Baselines			
ARMA	1.800	1.180	1412
Last observed	0.142	0.121	2189
EWMA	0.259	0.211	1147
NTT (Ablated)			
No aggregation	0.258	0.430	61
Fixed aggregation	0.055	0.134	115
Without packet size	0.001	8.688	94
Without delay	15.797	10.898	802

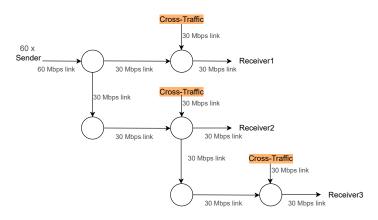
Mean Squared Error (MSE) for all NTT models and tasks for the single path topology (lower is better)

# NTT works on multi-path topologies



Fine-tuning data generation on multi-path topology

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Fine-tuning data generation on multi-path topology

- Path delays vary as per number of links
- Receiver ID as IP address proxy



# NTT works on multi-path topologies

Model	MSE: Delay Prediction all values×10 <sup>-3</sup>	# of Epochs trained
NTT		
Pre-trained + Fine-tune (full)	0.004	5
Pre-trained + Fine-tune (10%)	0.035	12
From scratch + Fine-tune (full)	5.2	10
From scratch $+$ Fine-tune $(10\%)$	8.2	15
Baselines		
ARMA	4.2	-
Last observed	11.2	-
EWMA	4.0	-
NTT (Ablated)		
Pre-trained + Fine-tune (full) : No Receiver ID	2.8	8
From scratch $+$ Fine-tune (full) : No Receiver ID	2.7	15

Fine-tuning NTT on the multi-path topology (lower is better)





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  - Learn on larger topologies.

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- Federated Learning
  - Share models, not data.
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- Continual learning
  - Re-train with time, prevent forgetting.
  - Learn evolved dynamics.



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- Learning network dynamics is possible
  - NTT learns network dynamics from packet sequences
  - Pre-trained NTT can be re-used easily
- Generalizing power of the NTT
  - Can generalize to new environments: Packet level
  - Can generalize to new tasks: Flow level