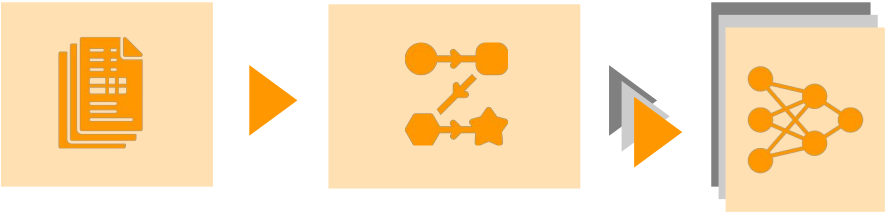
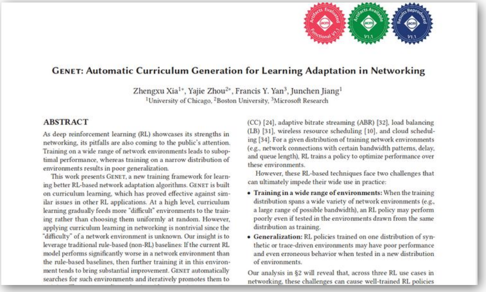
A New Hope for Network Model Generalization

ACM HotNets 2022



Alexander Dietmüller
Siddhant Ray
Romain Jacob
Laurent Vanbever

What do these systems have in common?



Video streaming, congestion control, and load balancing

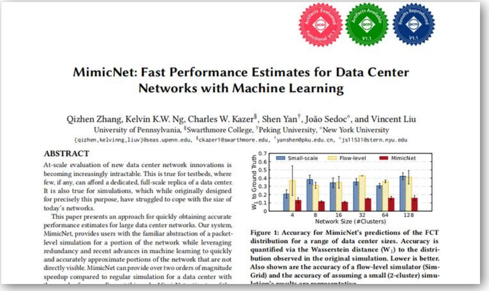
SIGCOMM'22

[GENET]

Video streaming

NSDI'20

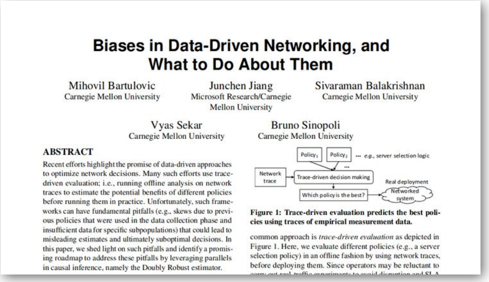
[Puffer]



Network simulation

SIGCOMM'21

[MimicNet]



Data-driven networking

HotNets'16

[Biases]

What do these systems have in common?

They have the same problem setting.

From past traffic ...

… an ML system estimates the state of the network to make a prediction.

MimicNet	packet (drop, latency, ECN)
Puffer	transmission time
GENET	bitrate for next chunk
…	

What do these systems have in common?

They have the same problem setting. But that’s about it.

From past traffic ...

… an ML system estimates the state of the network to make a prediction.

MimicNet	packet (drop, latency, ECN)
Puffer	transmission time
GENET	bitrate for next chunk
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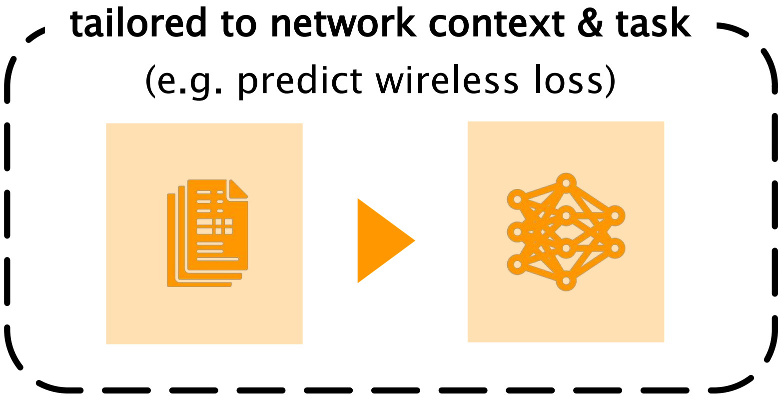
ML systems in networking do not generalize.

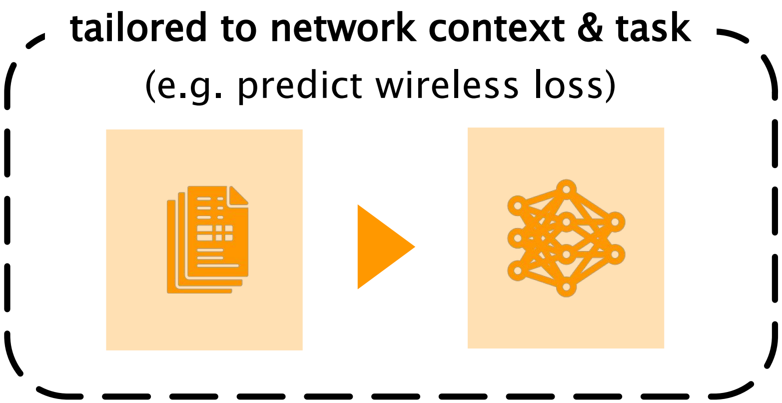


SO
WHAT

SO WHAT

are the consequences for ML in networking?

ML systems in networking do not generalize. This limits re-usability, forcing us to repeat data collection, model design, and training.



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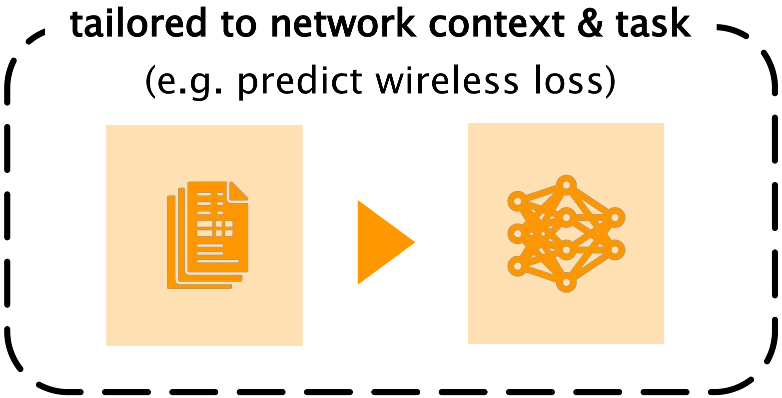

Same task *(predict loss)* with data from

a context in situ	✓	[Puffer]

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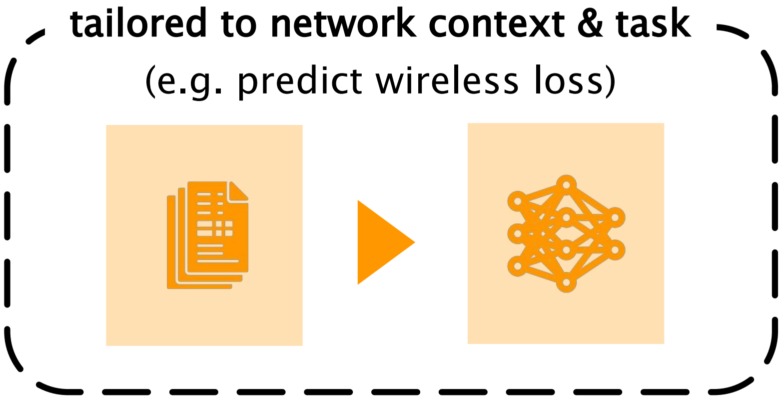

Same task *(predict loss)* with data from

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a similar context *(wireless)*	✓/✗	[GENET]

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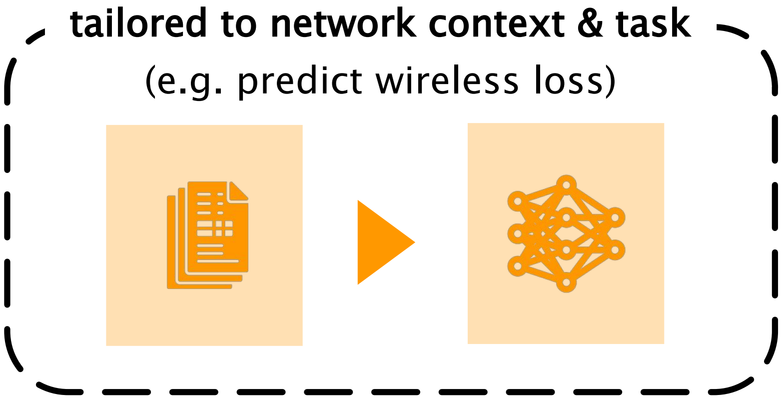

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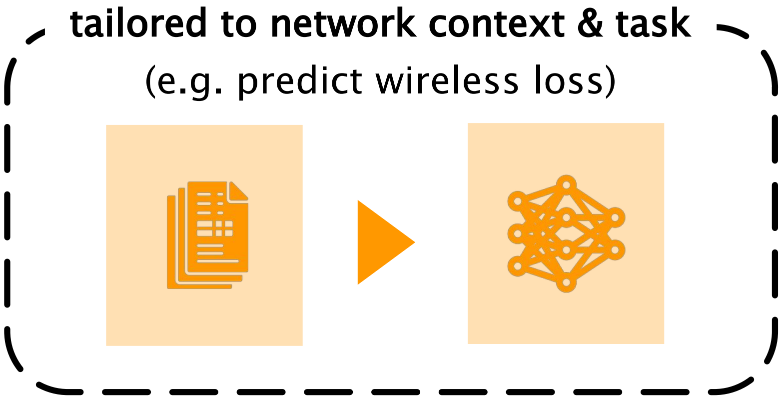

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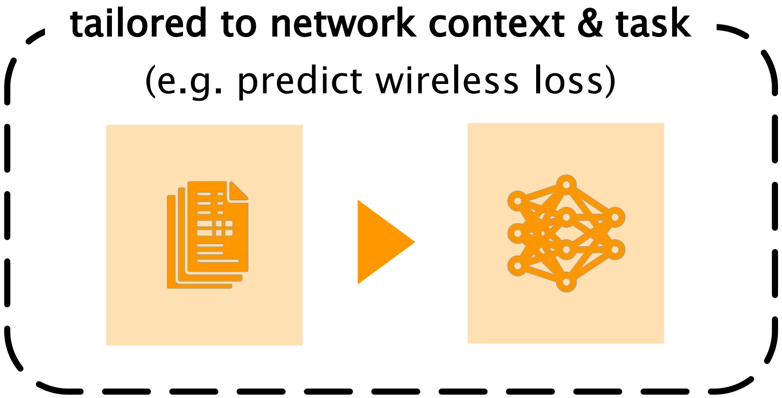

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a context in situ	✓	[Puffer]
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multiple contexts *(both)*	✗	

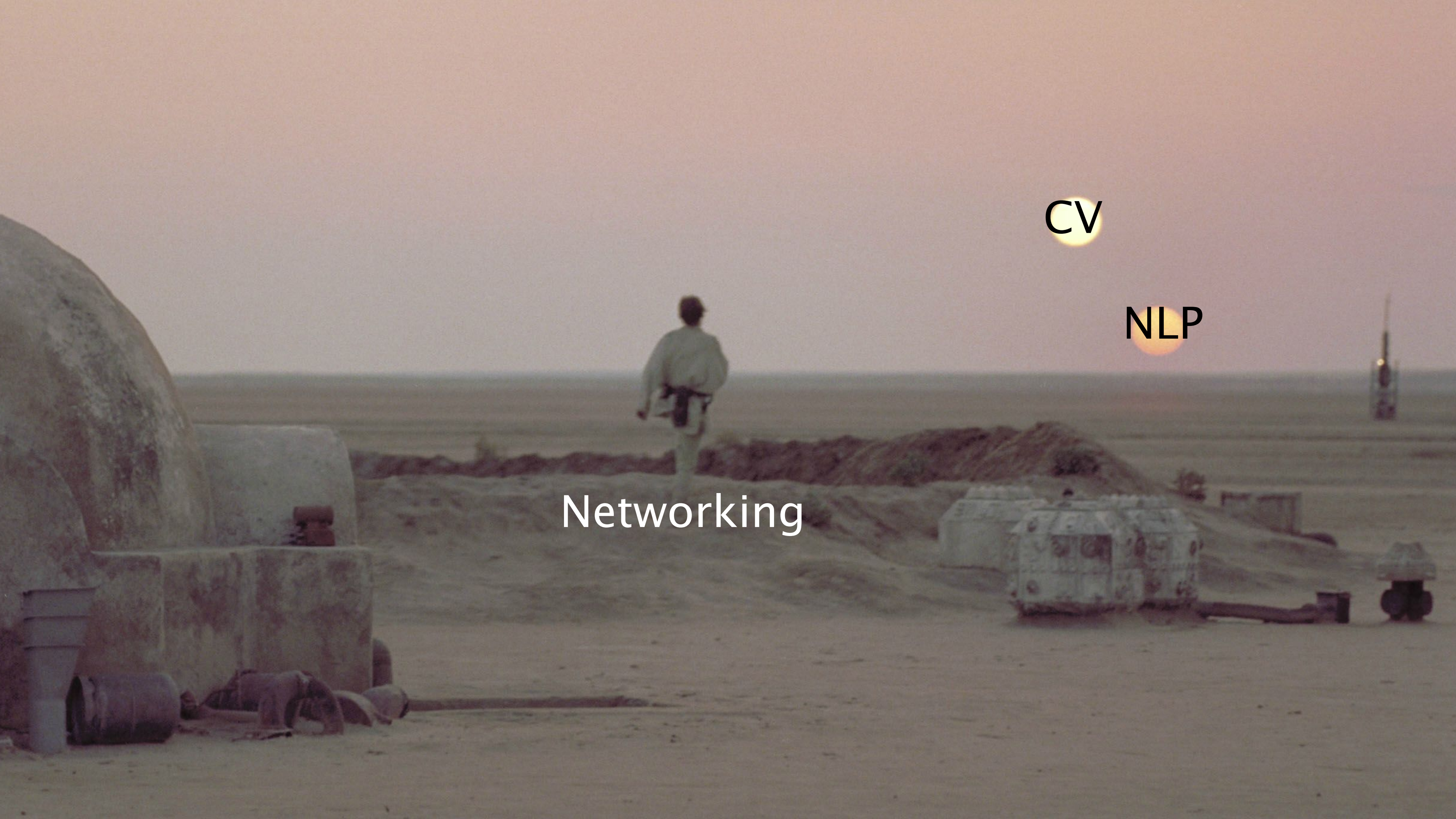
Different task *(e.g. predict delay)*

✗ (requires a completely new model and data)

Is there no way to get

- optimal performance
- for multiple contexts and different tasks
- without starting from scratch every time ?

A New Hope for Network Model Generalization


CV
NLP
Networking

In NLP and CV, Transformer-based architectures

generalize by learning to infer sequence context.

NLP: Natural Language Processing; CV: Computer Vision; Images generated by OpenAI Dall-E 2.

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Dall-E 2

input: (text)

output: (generated image)

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input:	(text)	*Hand me that stick!*	*Stick to that hand.*
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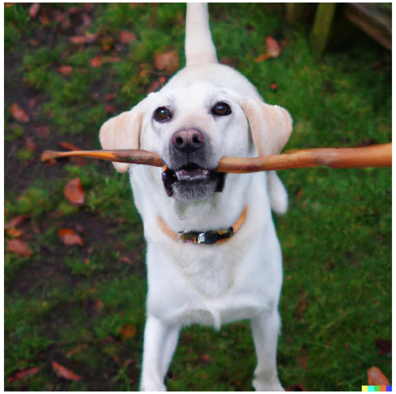

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Maybe we can get

- optimal performance
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A general pre-trained Transformer encoder
can be combined with specific fine-tuned decoders.

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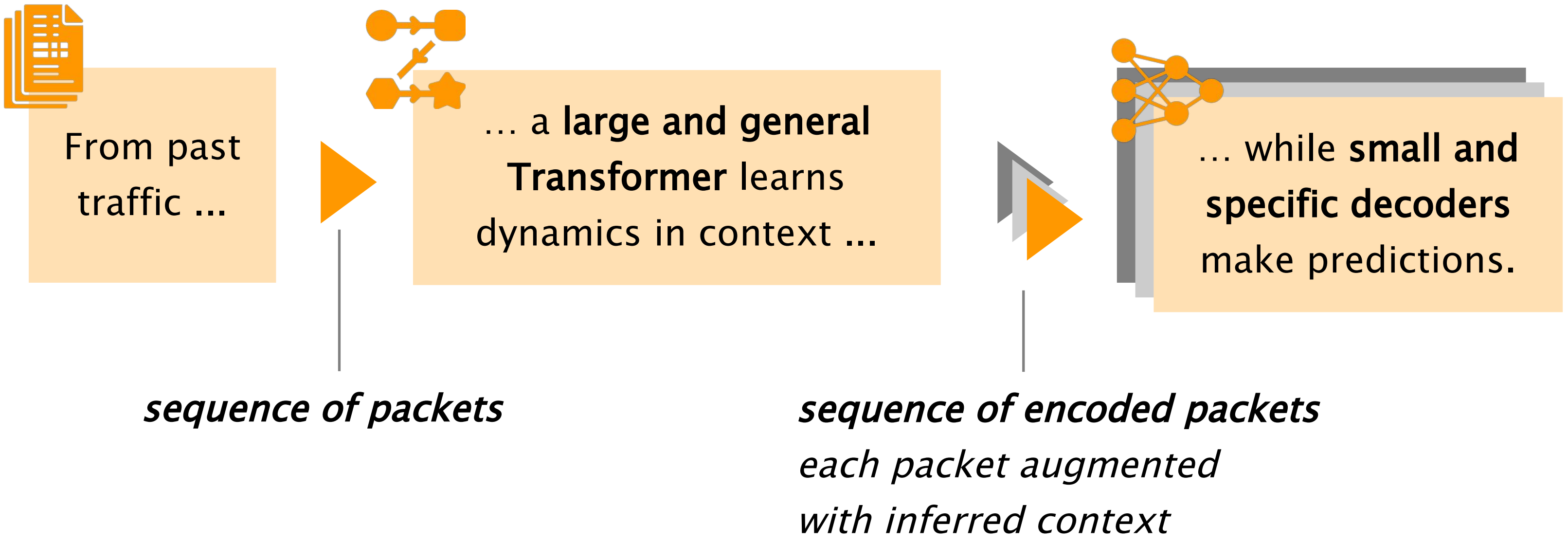
From past traffic ...

… a **large and general Transformer** learns dynamics in context ...

sequence of packets

sequence of encoded packets
each packet augmented
with inferred context

A general pre-trained Transformer encoder can be combined with specific fine-tuned decoders.



There is a way to get

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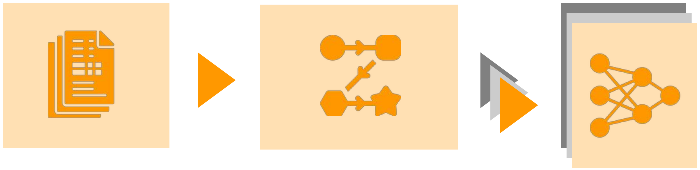
- for multiple contexts and different tasks
- without starting from scratch every time !

We cannot just copy an NLP Transformer:

a Network Traffic Transformer (NTT) must handle network challenges!



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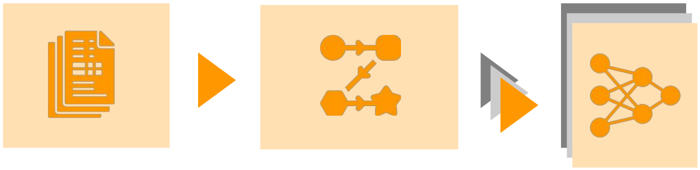

Challenge #1

Avoid packet features tailored to a specific task.

Challenge #2

Process long sequences without losing detail.

Challenge #3

Learn contextual dynamics during pre-training.

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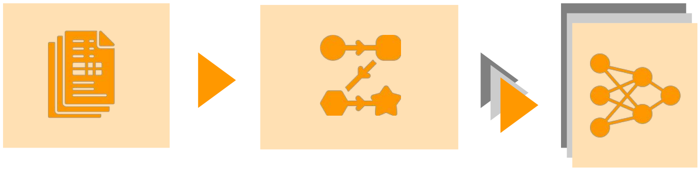

Challenge #1

Avoid packet features tailored to a specific task.

→ **learning features**

Challenge #2

Process long sequences without loosing detail.

→ **aggregate past packets hierarchically**

Challenge #3

Learn contextual dynamics during pre-training.

→ **pre-train to predict end-to-end delay**

In simulation, we observe first evidence

that networking could benefit from pre-trained models as well.

We pretrain, ...

context
30 senders and
a single shared
bottleneck

task
delay prediction

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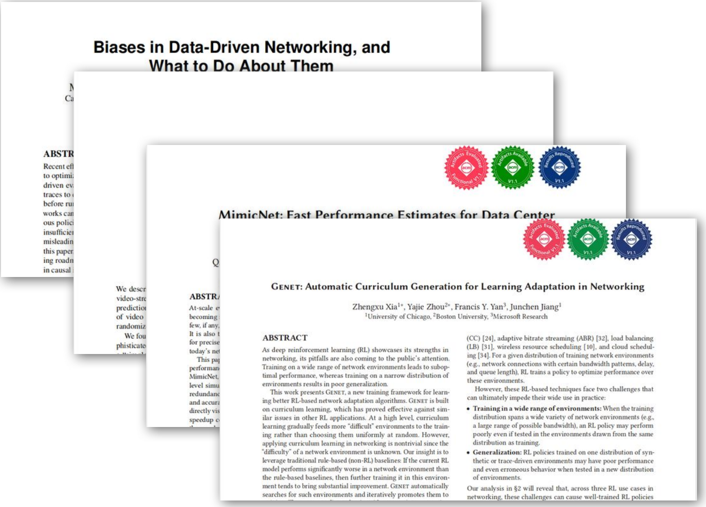
NTT *may* generalize.

What next?

Our simulation results are promising, and it is time to **use and evaluate NTT-based models in the real-world**.



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Create new models based-on NTT.

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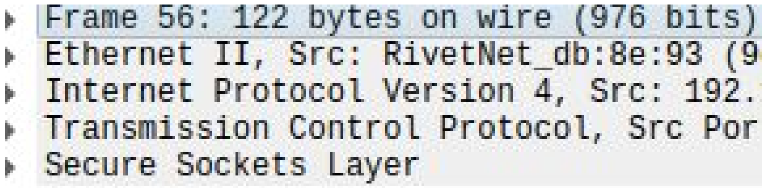

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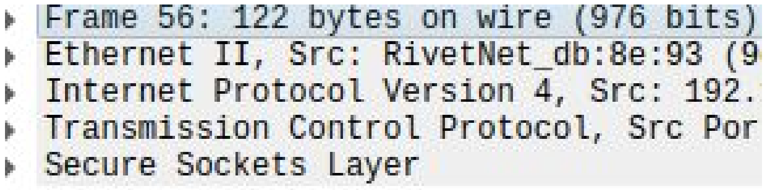

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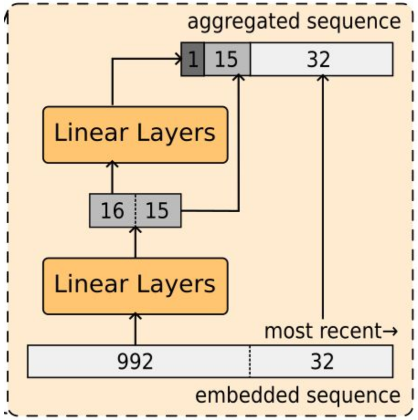

Which aggregation levels cover all significant network interactions?

Transformer models like NTT extract and compress information, **facilitating sharing and collaboration**.

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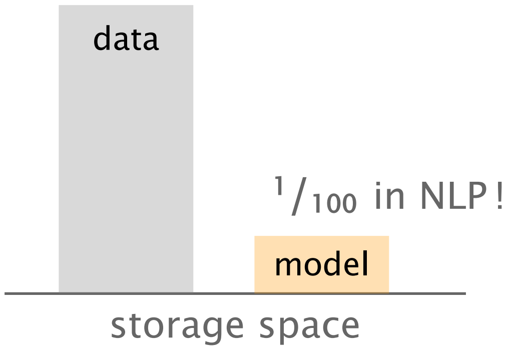

train from large traces every time

download a pre-trained model

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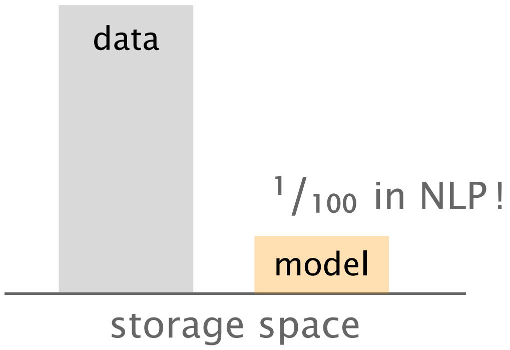

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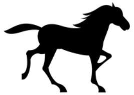

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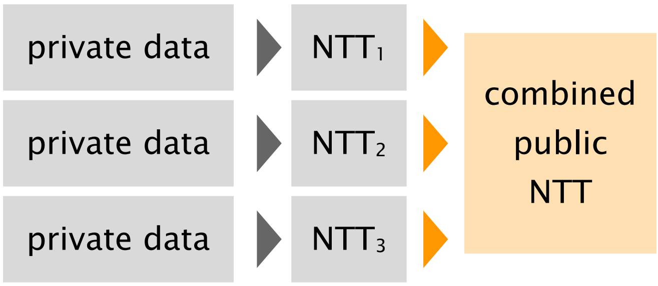

share private data

combine insights via federated learning

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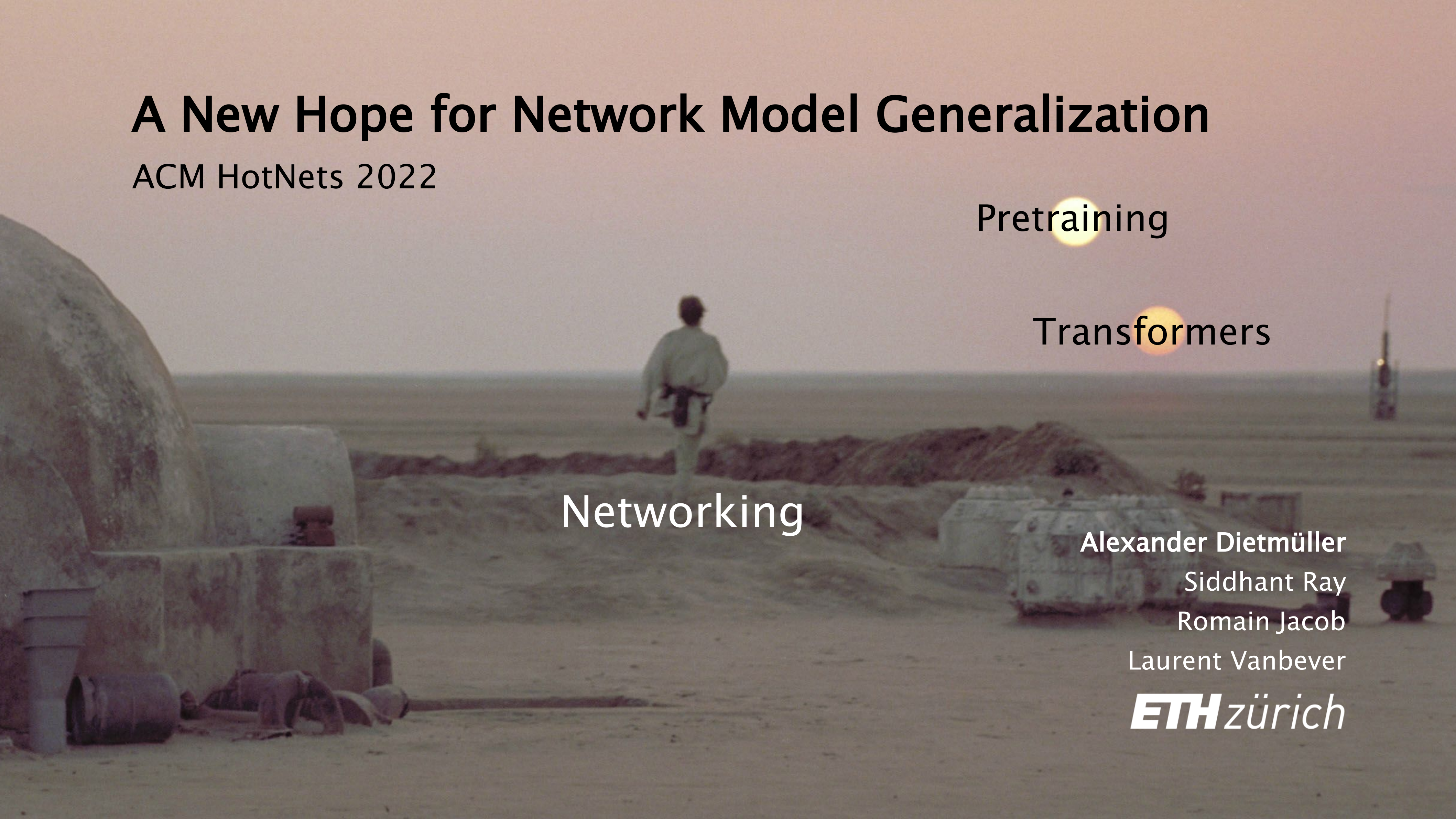

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