

# DIRT: Distributed Internal Regression Transformer

This research is financed by the CALCULUS project - Commonsense and Anticipation enriched Learning of Continuous representations

European Research Council Advanced Grant H2020-ERC-2017-ADG 788506

Nathan Cornille  
Damien Sileo  
Marie-Francine Moens

Department of Computer Science

November 9-12, 2020

# Context

March 2020

July 2020

November 2020



Abstract: paper  
idea

Negative results:  
paper stopped

NAISys 2020

# Motivation

 Improve **Natural Language Understanding**

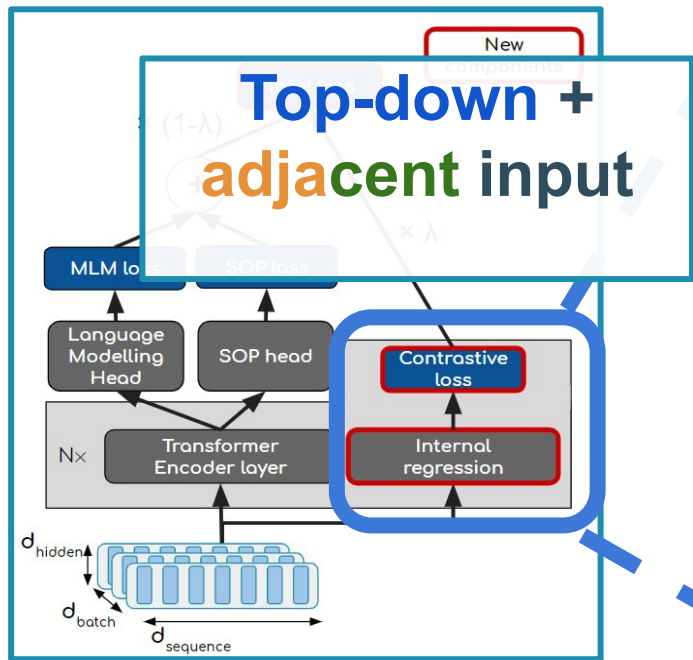


Improve quality of **general-purpose representations**

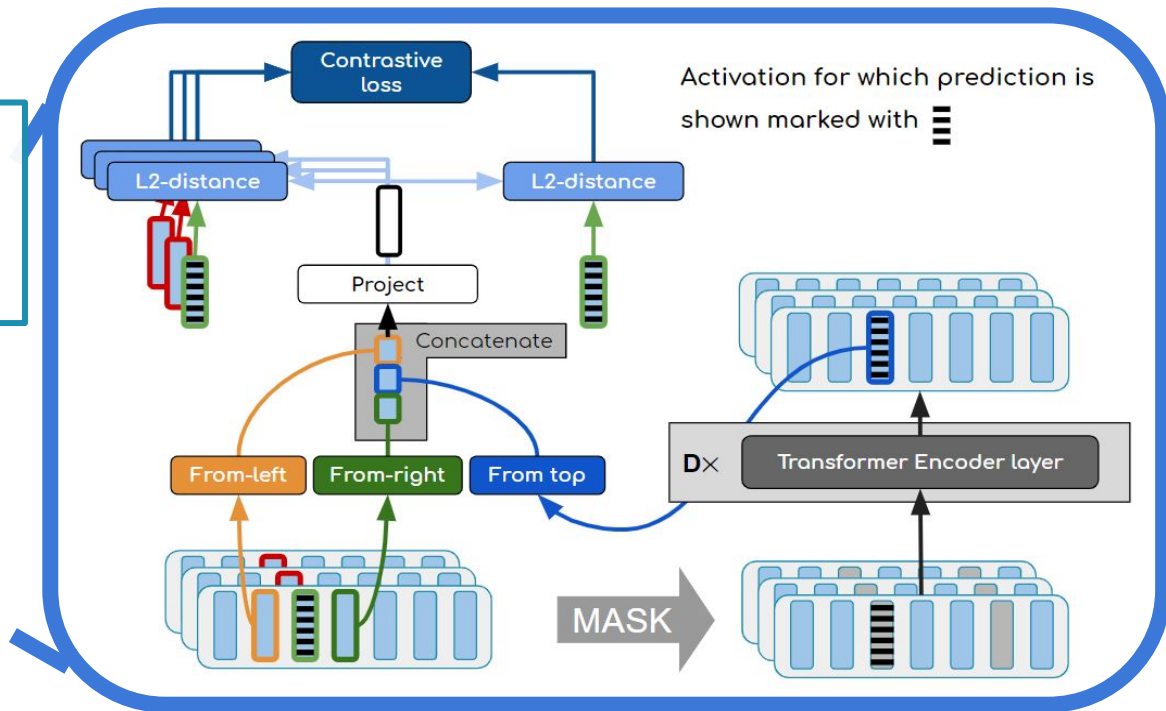


Train with internal self-prediction loss<sup>1,2,3,4</sup>

# Implementation



## Per layer loss



- Prevent “cheating” by the model
- **Bonus:** induce desirable “slow features”

# Results



# SuperGLUE<sup>5</sup> benchmark

$\lambda = 0$ (baseline)	61.2±0.7
$\lambda = 0.4$	<b>61.5±0.7</b>
$\lambda = 0.9$	60.9±0.9

**Negative result:** no significant improvement over baseline

	Avg	BoolQ Acc.	CB Acc./F1 Avg	COPA Acc.	MultiRC F1 <sub>a</sub> /EM Avg	ReCoRD F1/EM Avg	RTE Acc.	WiC Acc.	WSC Acc.	AX <sub>b</sub> MCC	AX <sub>g</sub> Acc./GPS
$\lambda = 0$ (baseline)	61.2±0.7	75.4±0.7	<b>71±4.5</b>	55±2.8	43.8±0.8	45.4±2.9	<b>71.7±0.9</b>	68.6±1	59.1±2.2	19.1±2	50.6±1.3/96.8±1.5
$\lambda = 0.4$	<b>61.5±0.7</b>	74.9±0.8	70.3±1.8	54.7±4.6	<b>44.4±0.3</b>	<b>48.2±1.3</b>	71.6±1.5	<b>68.7±0.9</b>	59.3±0.6	<b>19.2±1.3</b>	50.6±0.5/97.2±0.6
$\lambda = 0.9$	60.9±0.9	<b>75.7±0.7</b>	70.9±8.2	<b>55.3±2.5</b>	43.6±0.6	43.1±2.1	71.6±0.8	67.8±0.8	59.3±3.9	17.2±1.3	51.4±2.3/97.6±1.2
$\lambda = 1$	42±2.4	62.2±0	36.1±0	53.5±7.8	9.4±11.8	13.8±0.4	47.1±0.3	50±0	<b>63.5±0</b>	0±0	<b>51.7±X/100±X</b>
Most Frequent	47.7	62.2	36.1	55.0	30.4	32.0	52.7	50.0	<b>63.5</b>	0.0	50/100
CBoW	47.7	62.4	60.5	<b>63.0</b>	10.3	14.1	54.2	55.3	61.5	-0.4	50/100

# Internal loss

First layers are hardest to self-predict

Top-down signal doesn't add value

Figure 3: Evolution of DIR loss at different layers, shown for  $\lambda = 0.4$ .

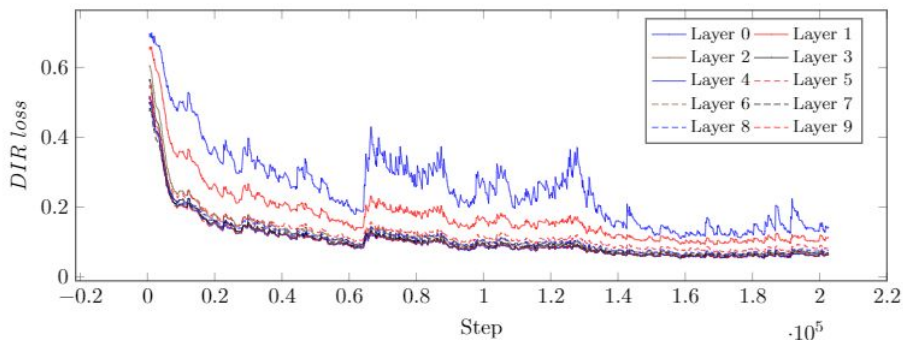
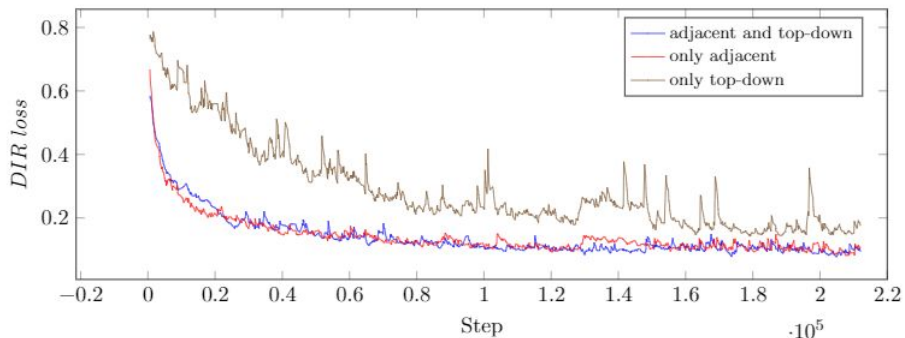


Figure 4: Inner self-prediction loss for different ablations of input for self-prediction.



# Lessons learned

# Lessons learned

- **Stepping back**
  - Actually complementary?
- **Contrastive loss red herring**
  - slow features  $\Leftrightarrow$  local input
  - **minmax objective** as alternative cheating-prevention
    - more biologically plausible too?

# References

1. K. L. Downing. Predictive models in the brain. *Connection Science*, 21(1):39–74, 3 2009.
2. L. Gisoni, B. Mohr, and F. Pulvermüller. Prediction mechanisms in motor and auditory areas and their role in sound perception and language understanding. *NeuroImage*, 199:206–216, 10 2019.
3. A. Modi, I. Titov, V. Demberg, A. Sayeed, and M. Pinkal. Modeling Semantic Expectation: Using Script Knowledge for Referent Prediction. *Transactions of the Association for Computational Linguistics*, 5:31–44, 12 2017.
4. A. F. Morse, H. Svensson, and T. Ziemke. Representation as Internal Simulation : A Minimalistic Robotic Model, 2009.
5. A. Wang, Y. Pruksachatkun, N. Nangia, A. Singh, J. Michael, F. Hill, O. Levy, and S. R. Bowman. SuperGLUE: A Stickier Benchmark for General-Purpose Language Understanding Systems. 5 2019.

# DIRT: Distributed Internal Regression Transformer

- Context
- Motivation
- Implementation
- Results
- Lessons learned







# Goal hierarchy

-  Better world

-  Internal self-prediction loss (this work)



# Goal hierarchy

-  Better world
-  Increased automation
-  Better language-understanding machines
-  Better general-purpose NLU representations
-  neuro-for-AI
-  Internal self-prediction loss (this work)

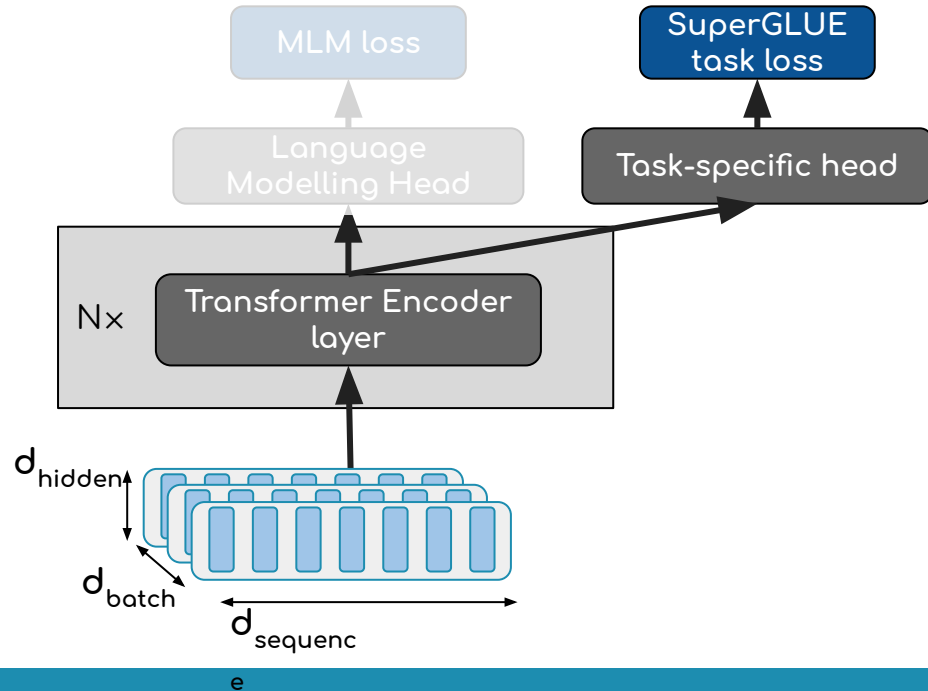




# Baseline Transformer

Step 1: Pretraining on massive unlabeled data

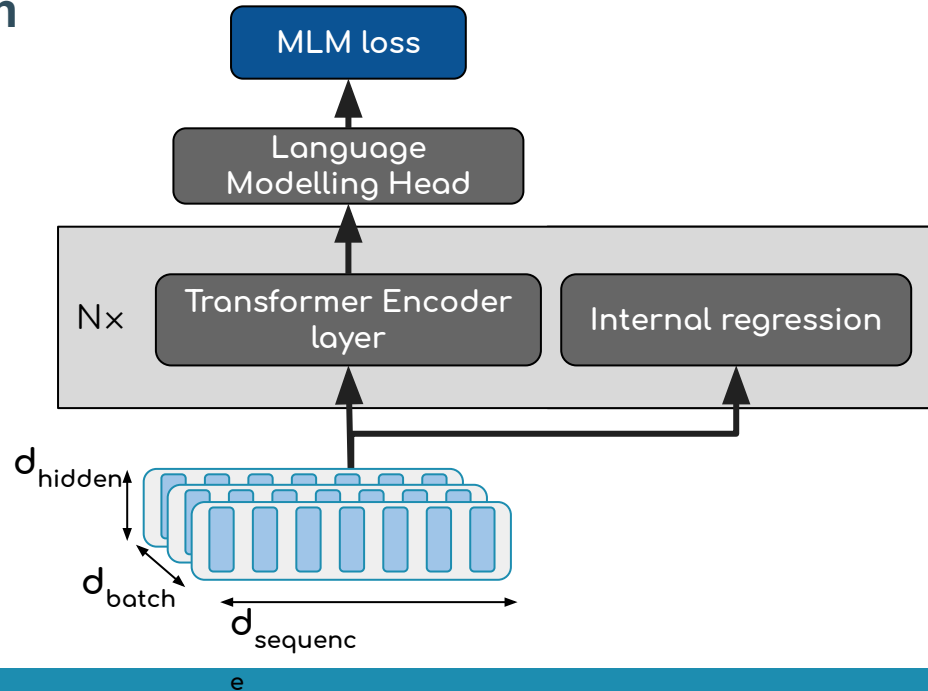
Step 2: Finetune pretrained model on variety of downstream tasks





# Proposed extension

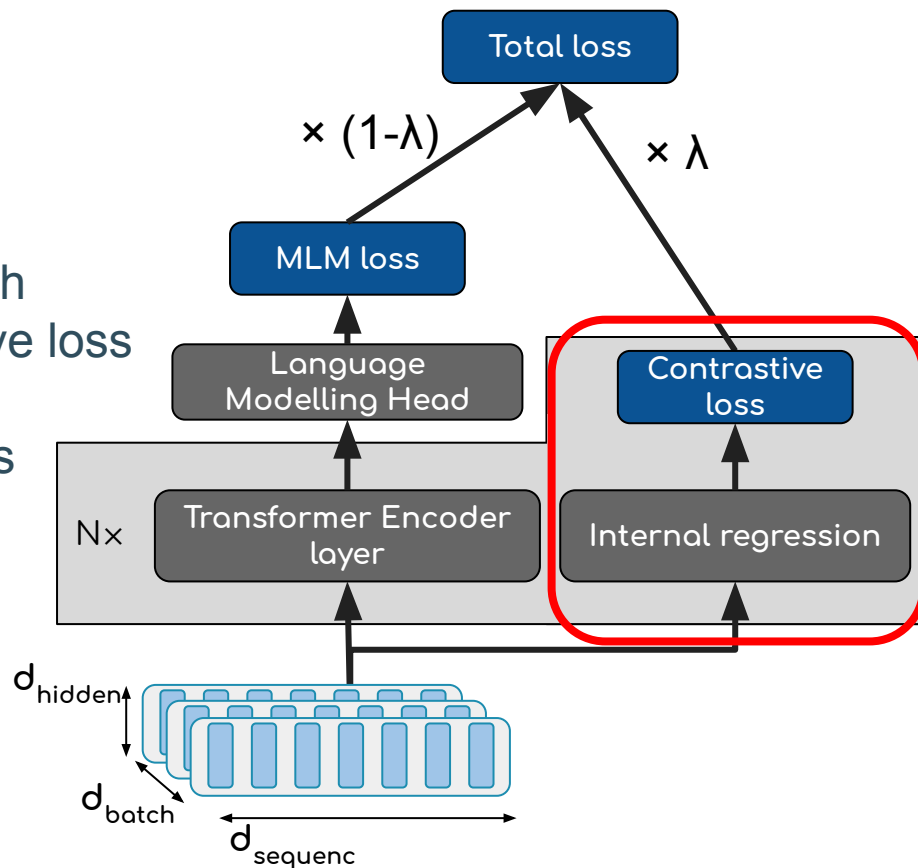
## Distributed Internal Regression Transformer (DIRT)





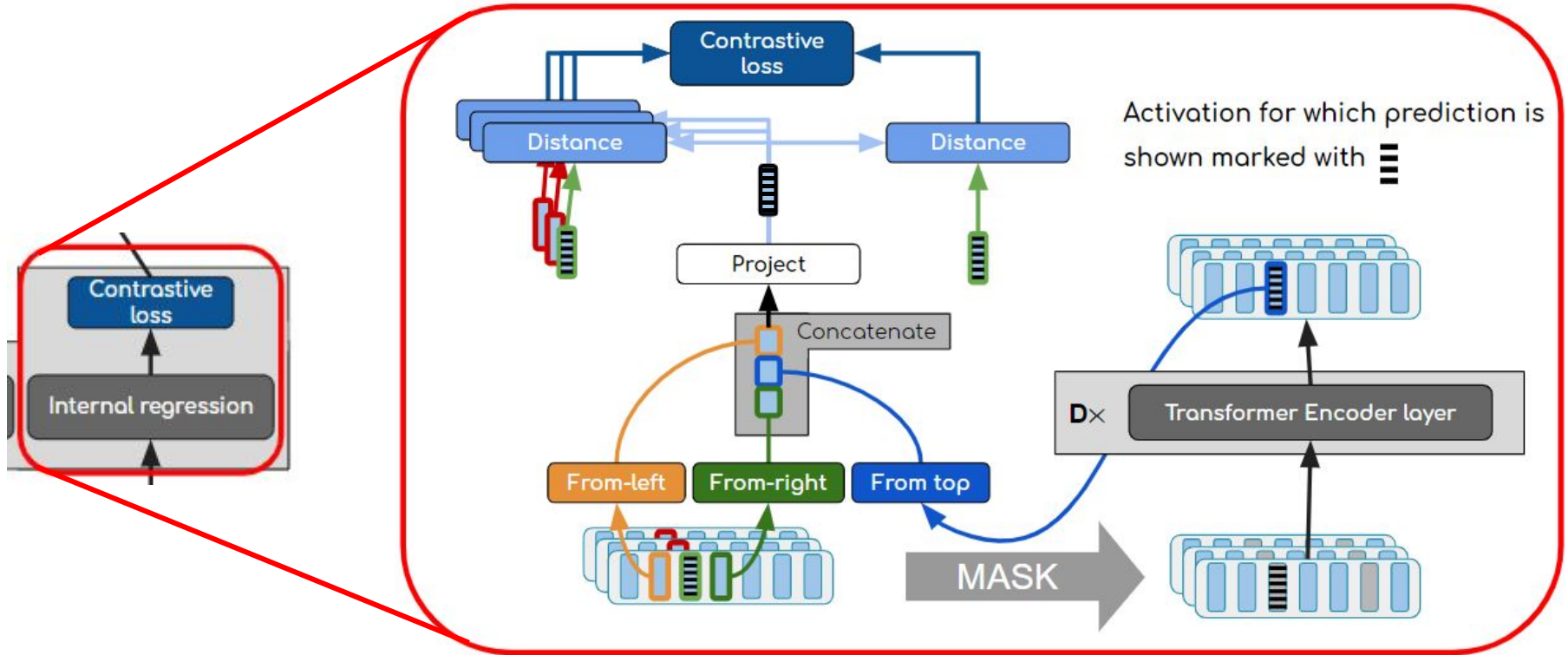
# DIRT-as-objective

1. Start with pretrained weights
2. Do **additional pretraining** with anticipation-inspired contrastive loss
3. Finetune on downstream tasks





# Detailed view

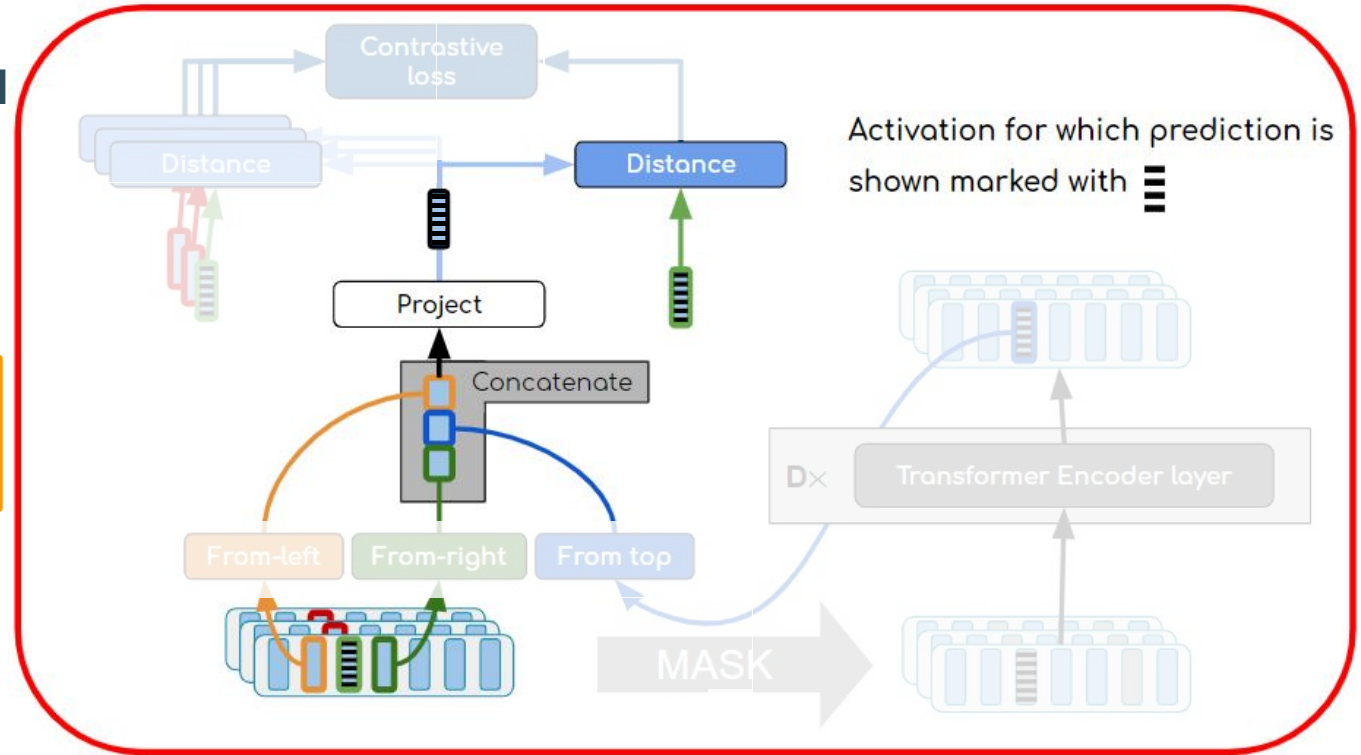




# Detailed view

## Porting to NLU model

Autoregressing to masked internal states



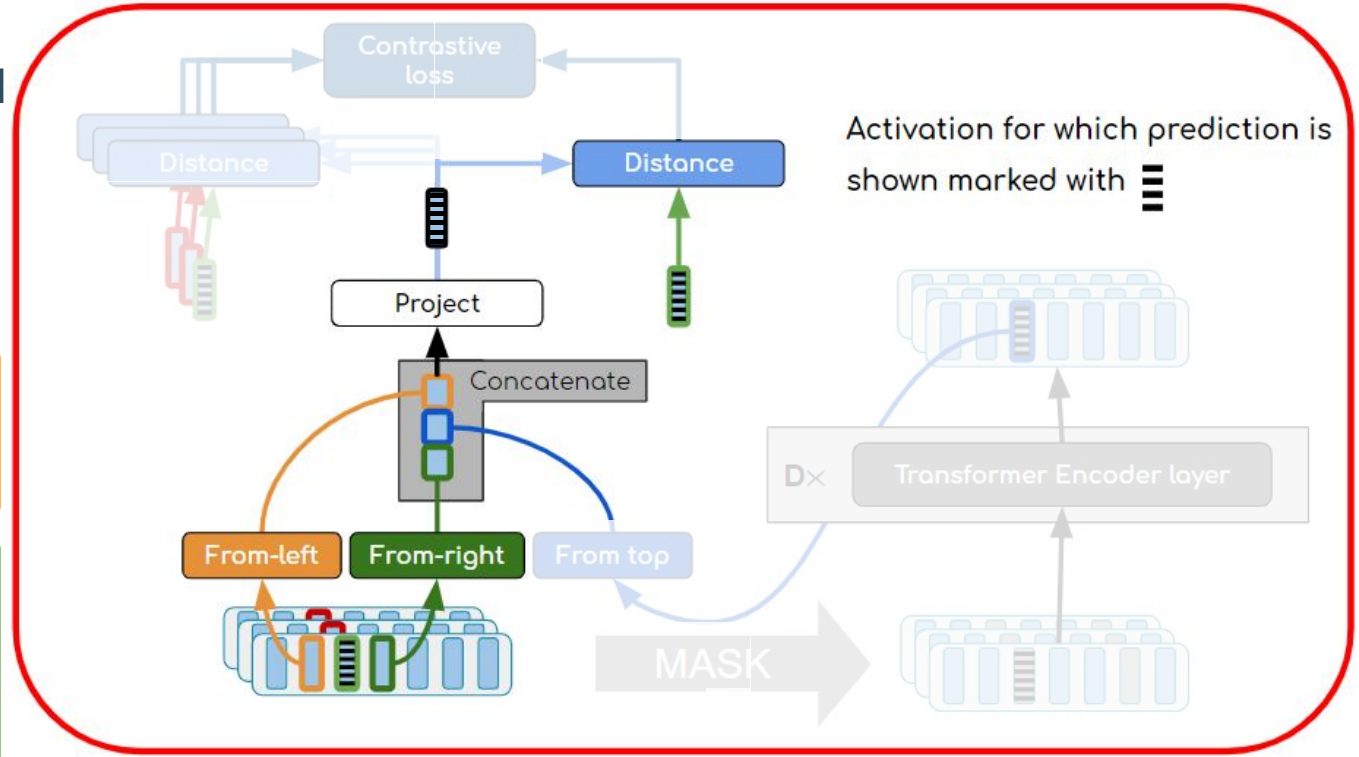


# Detailed view

## Porting to NLU model

Autoregressing to masked internal states

Input from neighbouring timesteps + top-down timesteps



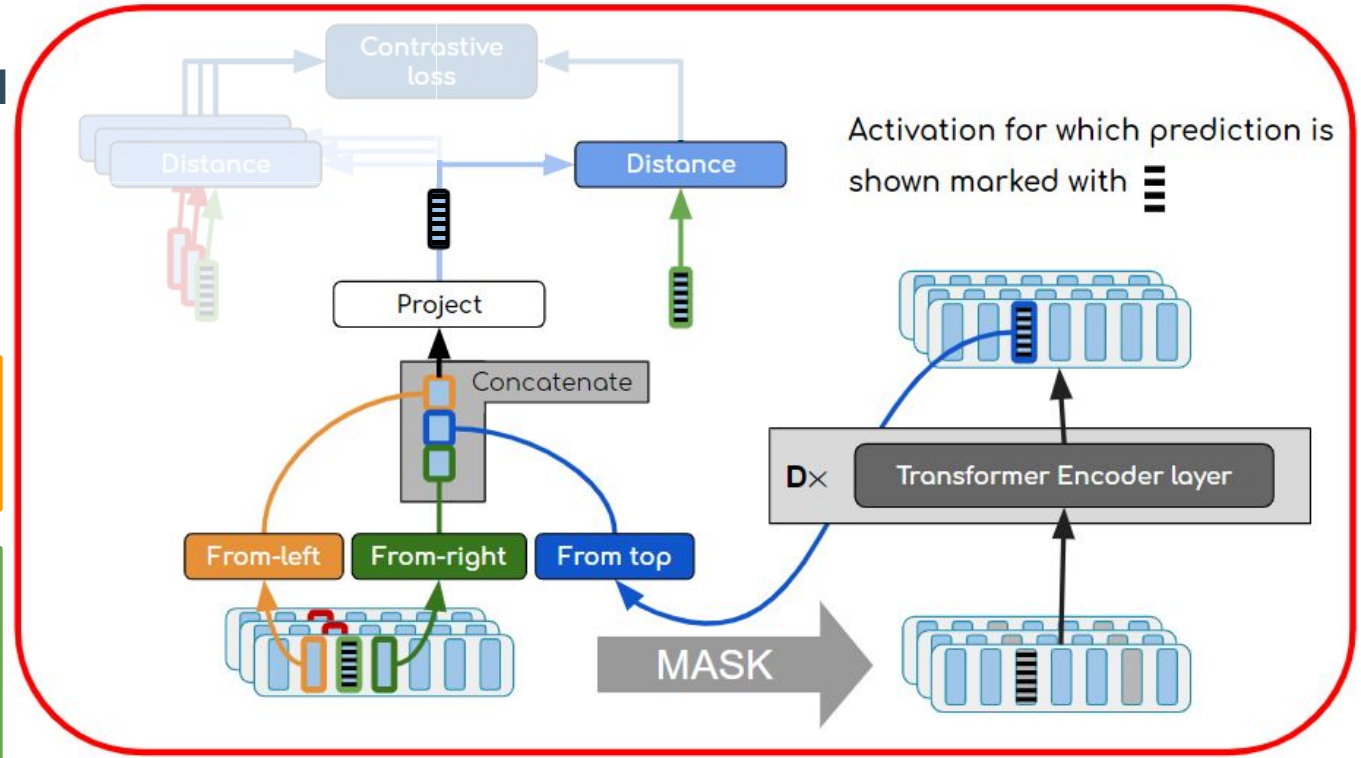


# Detailed view

## Porting to NLU model

Autoregressing to masked internal states

Input from neighbouring timesteps + top-down timesteps





# Detailed view

## Porting to NLU model

### Internal losses

- Grounding via contrasting

### Autoregressing to masked internal states

Input from neighbouring timesteps + top-down timesteps

