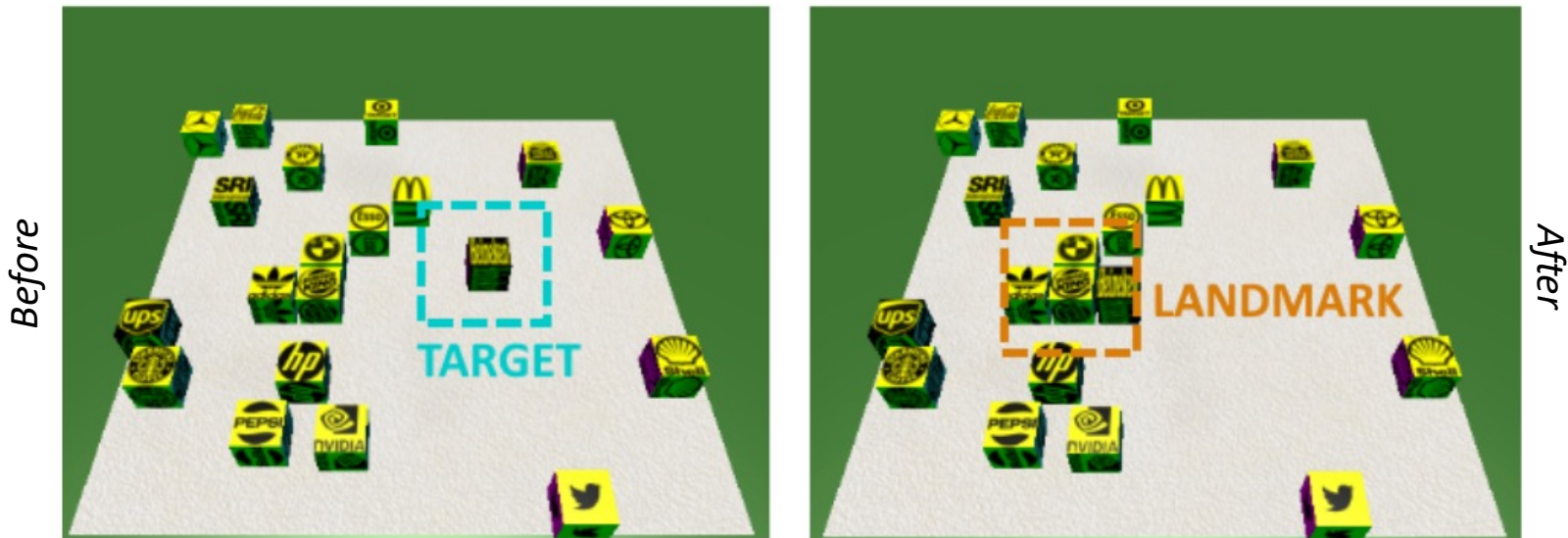


# Generating Landmark-based Manipulation Instructions from Image Pairs

Sina Zarrieß<sup>1</sup>, Henrik Voigt<sup>1</sup>, David Schlangen<sup>2</sup> and Philipp Sadler<sup>2</sup>

# Introduction

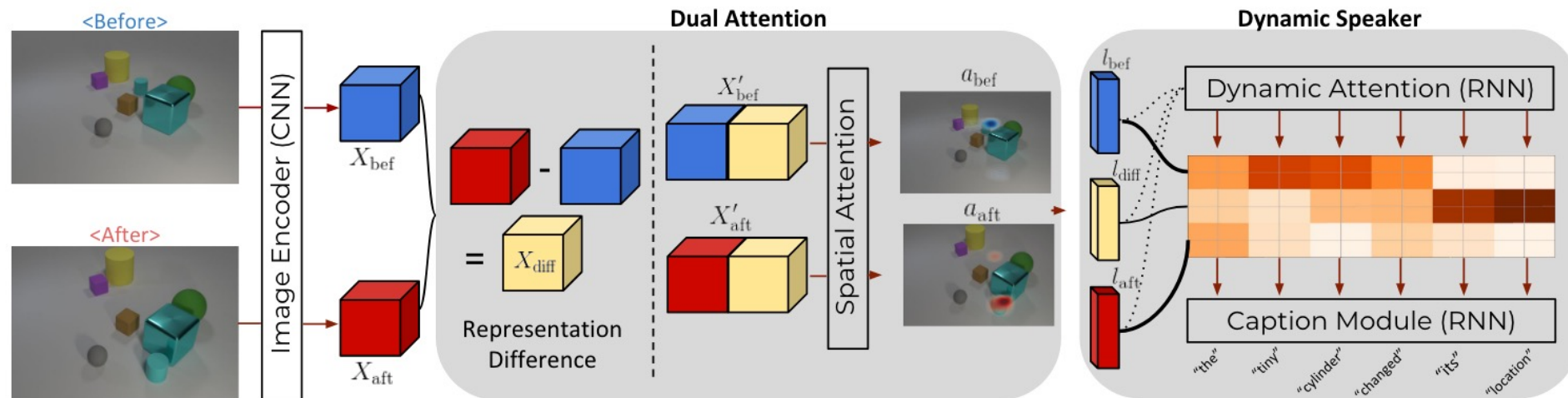
How to generate correct landmark references in manipulation instructions from image pairs?



GT: “Place the **Heineken** box so that it touches the **Burger King** box on the right side”

# Models: DUDA

- Park et al. (2019) used a Dual Dynamic Attention Model (DUDA) to articulate changes in image pairs

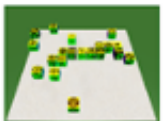


# Models: Self-Attention

How can we feed the images as useful inputs to a transformer?

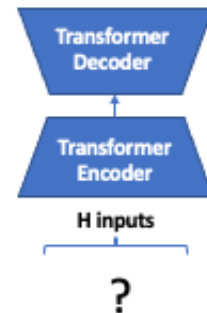


BEFORE



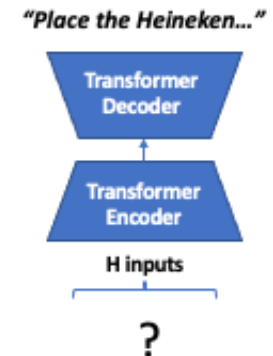
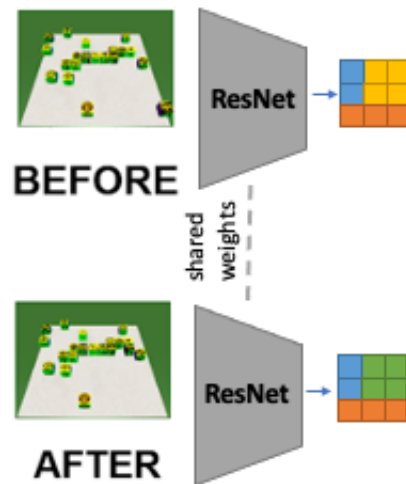
AFTER

*"Place the Heineken..."*



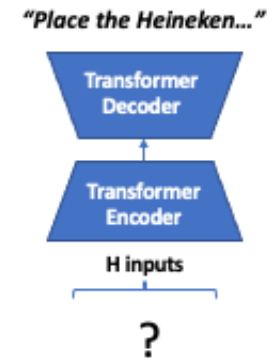
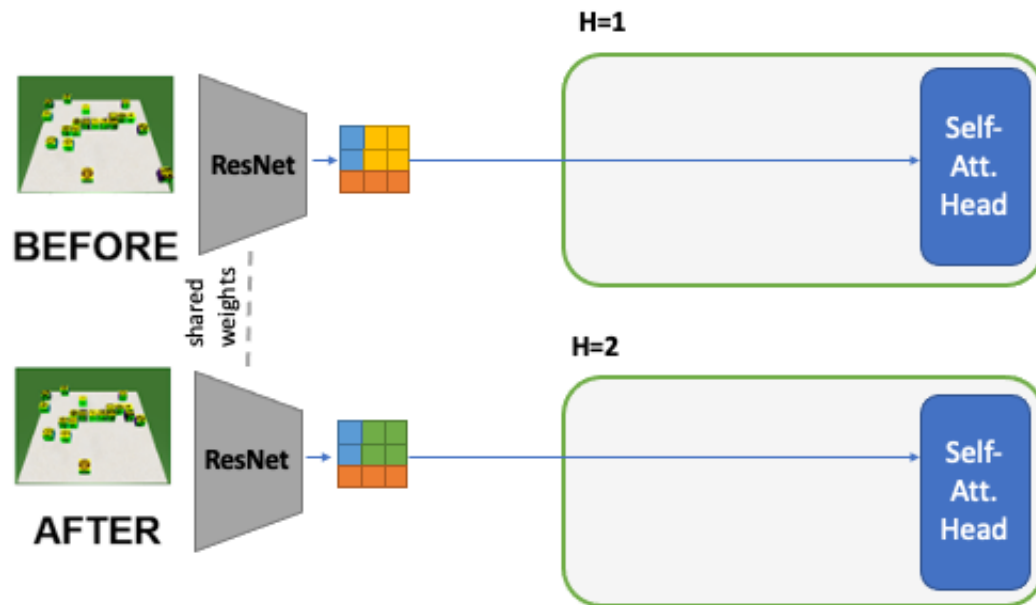
# Models: Self-Attention

How can we feed the images as useful inputs to a transformer?



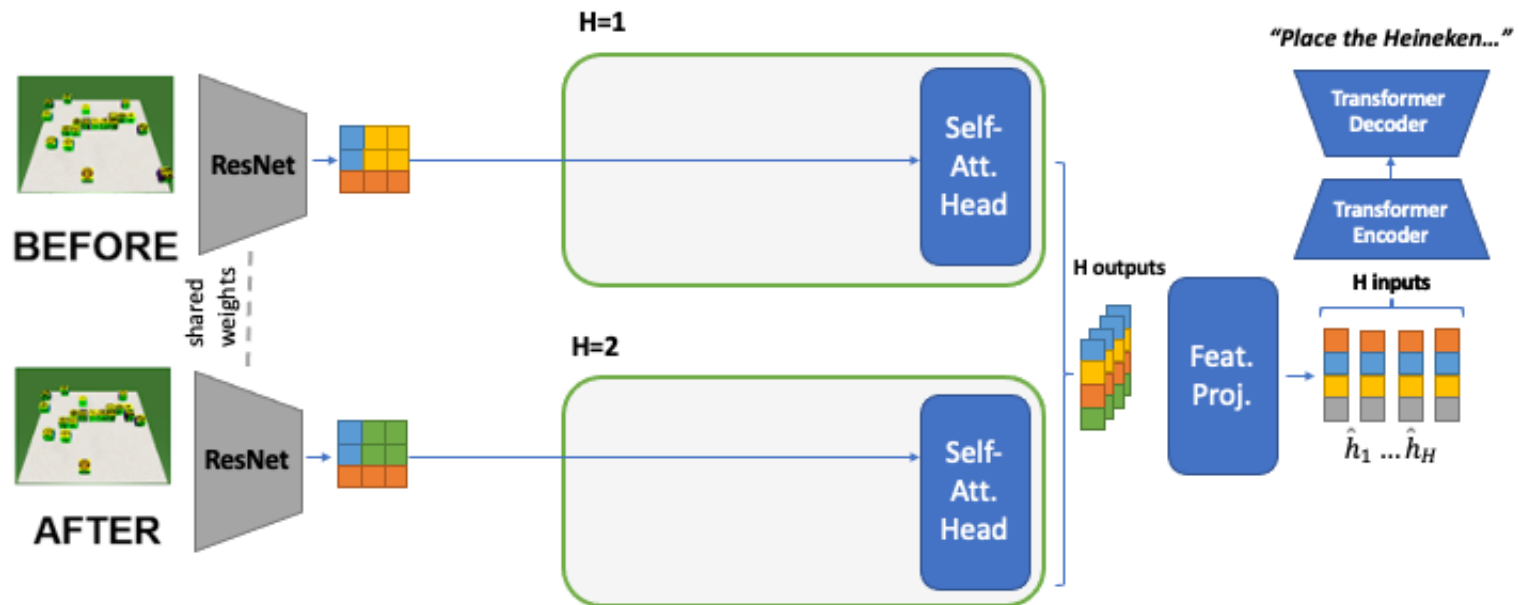
# Models: Self-Attention

How can we feed the images as useful inputs to a transformer?



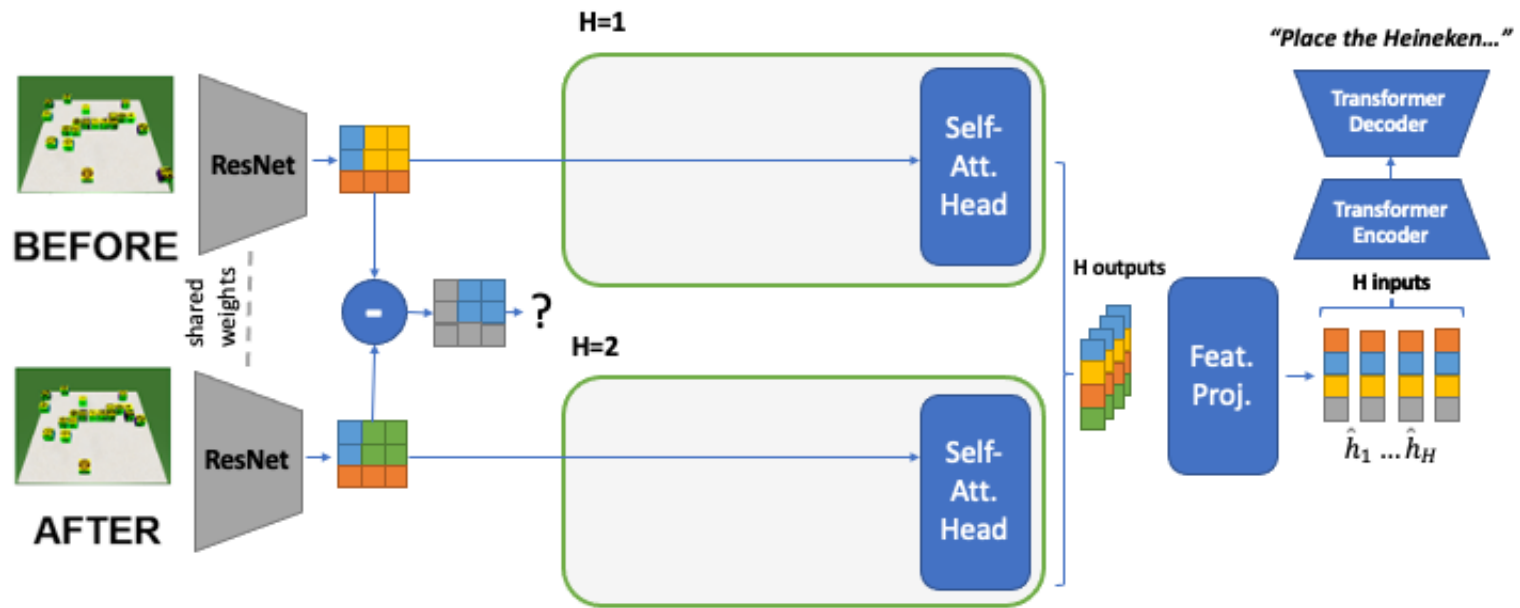
# Models: Self-Attention

How can we feed the images as useful inputs to a transformer?



# Models: Self-Attention

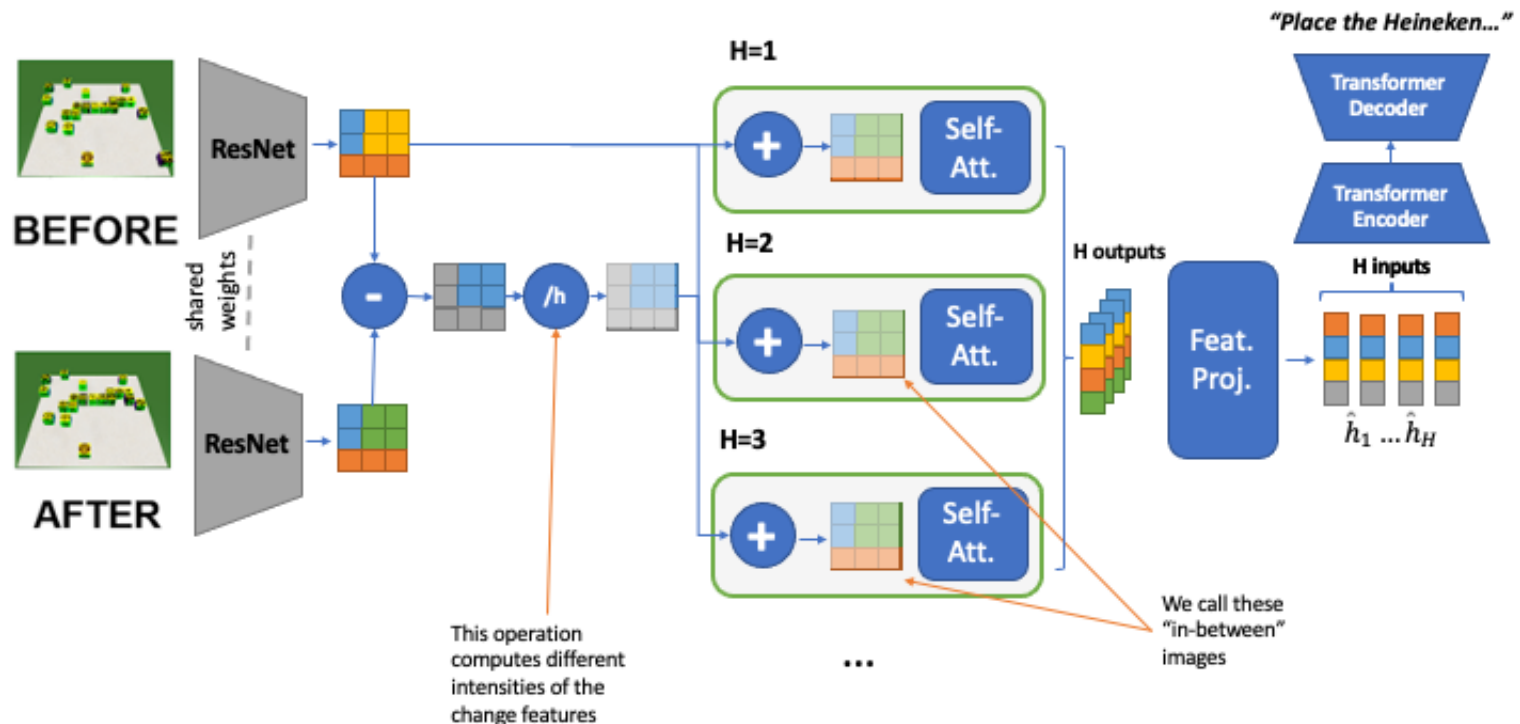
How can we use the „change“ features for self-attention heads?





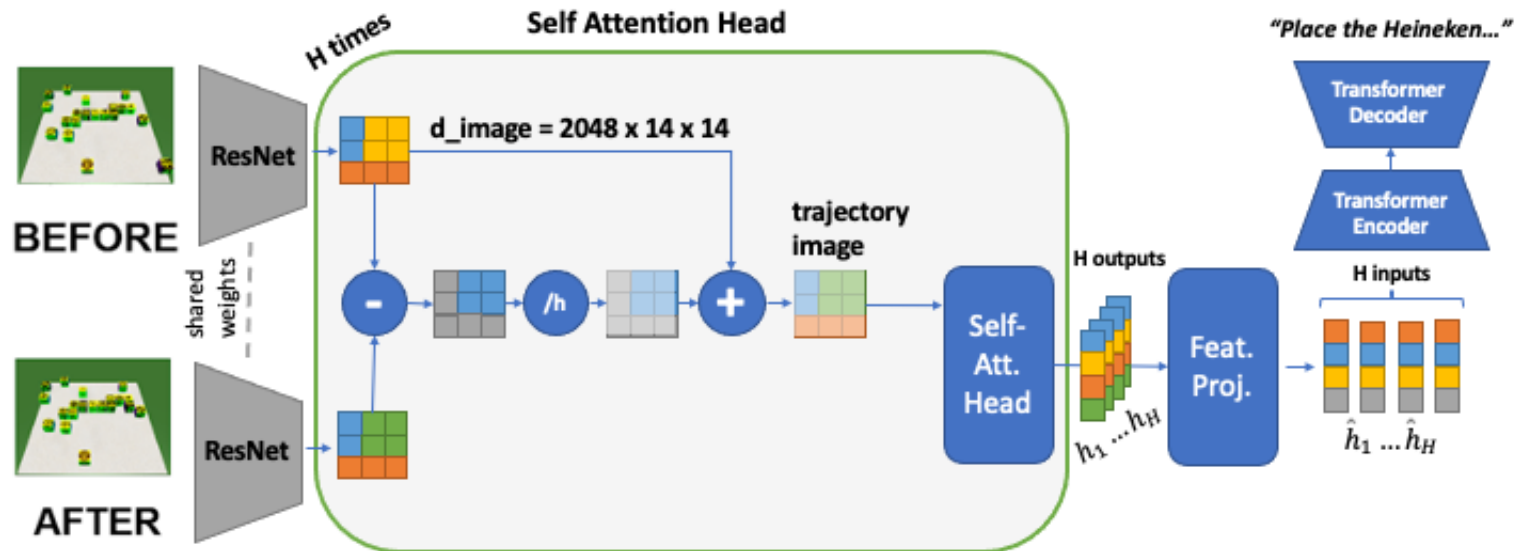
# Models: Self-Attention

How can we use the „change“ features for self-attention heads?



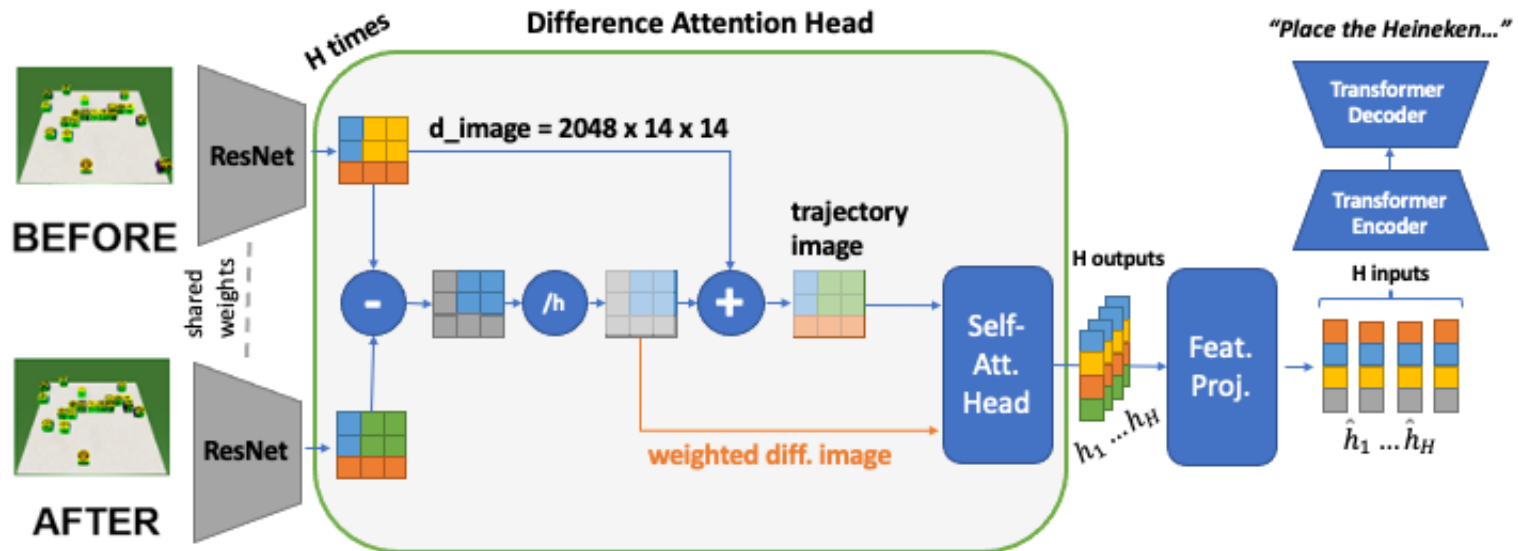
# Models: Self-Attention

How can we use the „change“ features for self-attention heads?



# Models: Difference(-guided)-Attention

Is cross-attention a powerful application here?



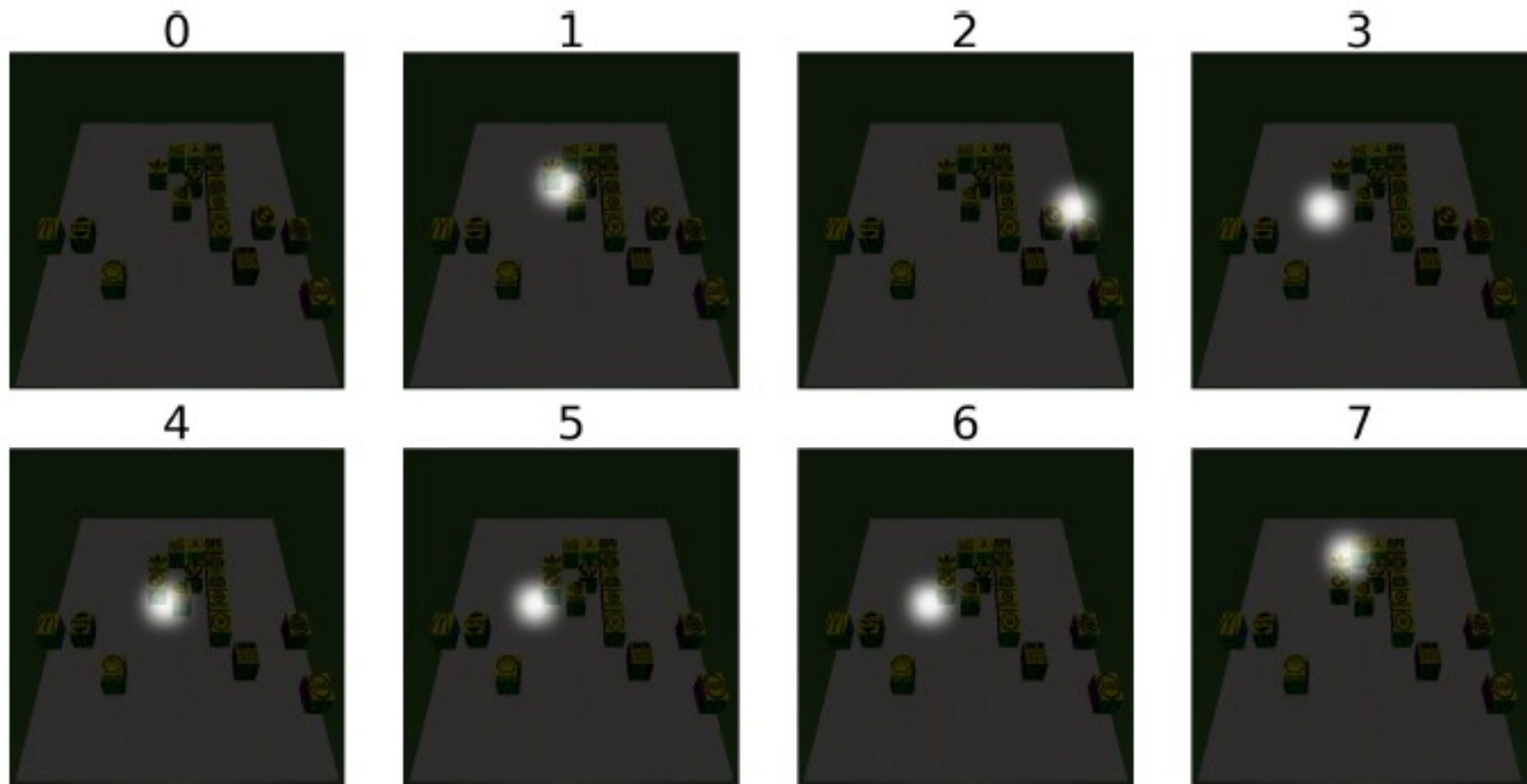
# Results and Discussion

- We observe that difference attention with “in-between images” gives a very clear performance boost for the realization of landmark references

Model	B	M	C	Target	Landm	Spatial
LSTM+Att*	0.38	0.28	0.27	0.11	0.28	-
DUDA	0.53	0.37	0.96	0.59	0.42	0.66
TF-self-att-2	0.34	0.28	0.35	0.19	0.26	0.76
TF-self-att-8	0.44	0.32	0.66	0.37	0.45	0.72
TF-diff-att-2	0.55	0.38	1.06	0.73	0.40	0.80
<b>TF-diff-att-8</b>	<b>0.68</b>	<b>0.43</b>	<b>1.52</b>	<b>0.86</b>	<b>0.73</b>	<b>0.83</b>

Table 1: BLOCKS results: B(LEU-4), M(eteor), C(ider) and word accuracies (see Section 3.3), LSTM+Att\* as reported in [Rojowiec et al. \(2020\)](#).

# Example Attention for TF-diff-att-8



# Additional Results

- Jhamtani and Berg-Kirkpatrick (2018) took surveillance images to detect and articulate changes in images



„4 additional people  
are present in after  
photo"

# Additional Results

- the differences between models on Spot-the-diff are generally much smaller but our model performs best

Model	B	M	C	S
DUDA*	0.081	0.115	0.34	-
FCC*	0.099	0.129	0.368	-
SDCM*	0.098	0.127	0.363	-
DDLA*	0.085	0.12	0.328	-
M-VAM + RAF*	0.111	0.129	0.425	0.171
TF-self-att-2	0.109	0.135	0.777	0.197
TF-self-att-8	0.110	0.136	0.786	0.191
<b>TF-diff-att-2</b>	<b>0.117</b>	<b>0.137</b>	<b>0.843</b>	<b>0.205</b>
TF-diff-att-8	0.113	0.136	0.842	0.202

Table 2: Spot-the-diff results: B(LEU-4), M(eteor), C(IDEr), S(PICE). \*Models as reported in [Shi et al. \(2020\)](#)

# Conclusion

- difference attention heads help transformers greatly to produce landmark based manipulation instructions
- the results are in line with other approaches (Herdade et al. 2019, Park et al. 2019, Cornia et al. 2020)
- n-gram overlap metrics can be only an auxiliary measure for instruction generation



# Thanks for listening!

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