

# What Happened 3 Seconds Ago? Inferring the Past with Thermal Imaging

THU-AM-060



Zitian Tang<sup>1</sup>



Wenjie Ye<sup>1</sup>



Wei-Chiu Ma<sup>2</sup>

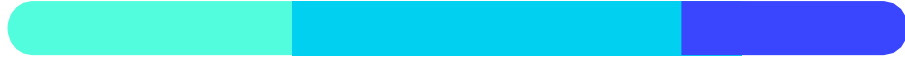


Hang Zhao<sup>1,3</sup>

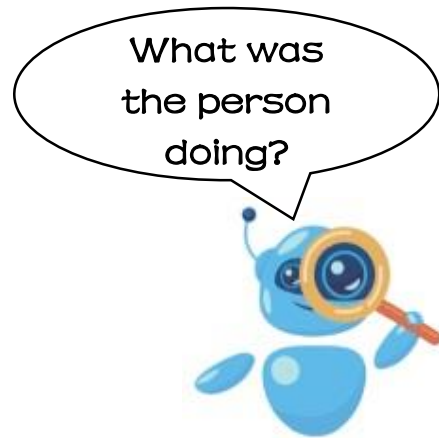
<sup>1</sup>Tsinghua University, IIS    <sup>2</sup>MIT, CSAIL    <sup>3</sup>Shanghai Qi Zhi Institute



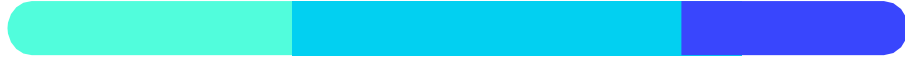
# Motivation



Can you tell what the person was doing 3 seconds ago?



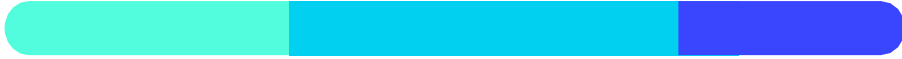
# Motivation



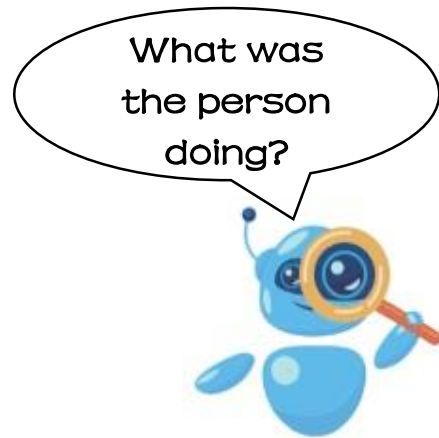
Heat transfers to the object during human-object interaction



# Motivation

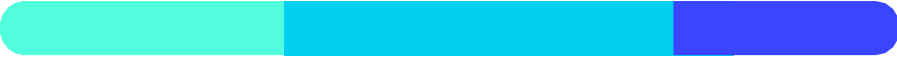


With a thermal image, the answer can be certain



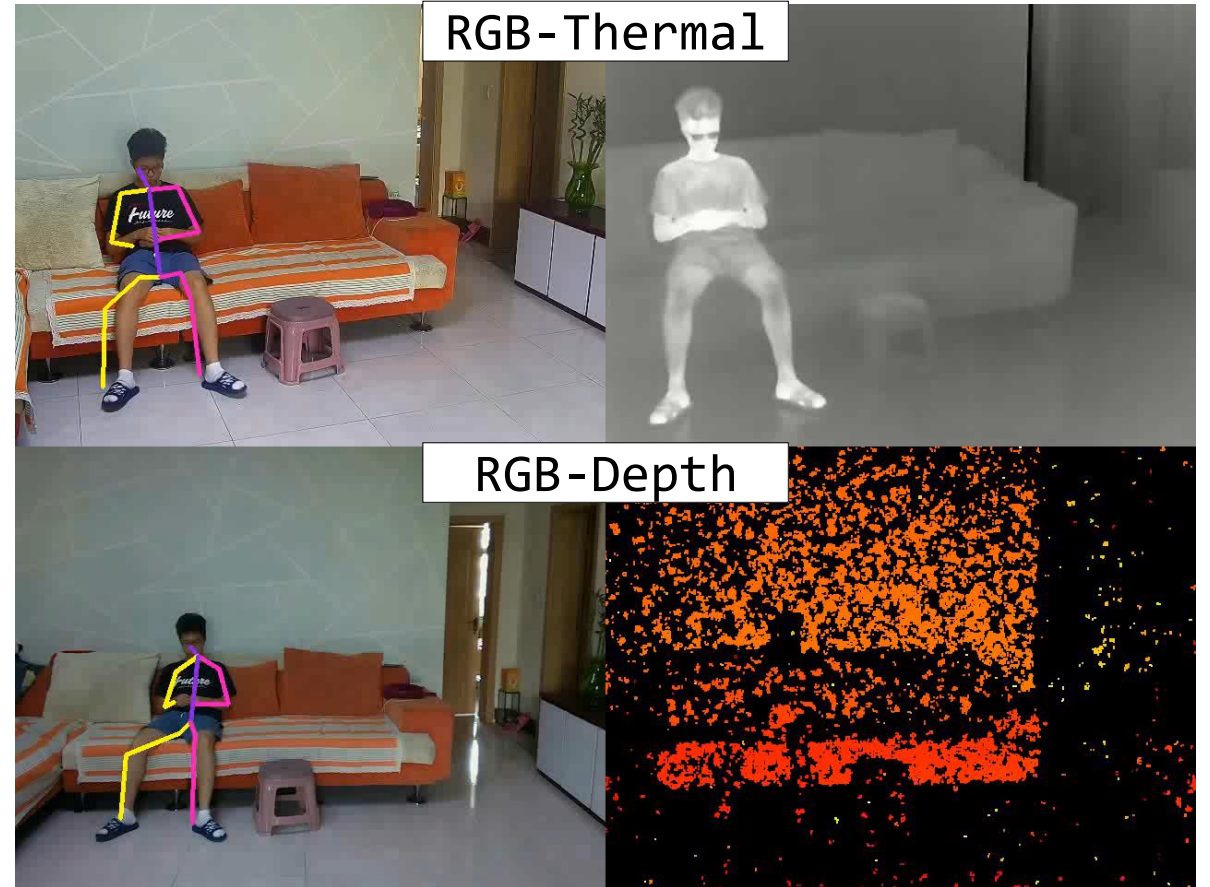


# Thermal Indoor Motion Dataset

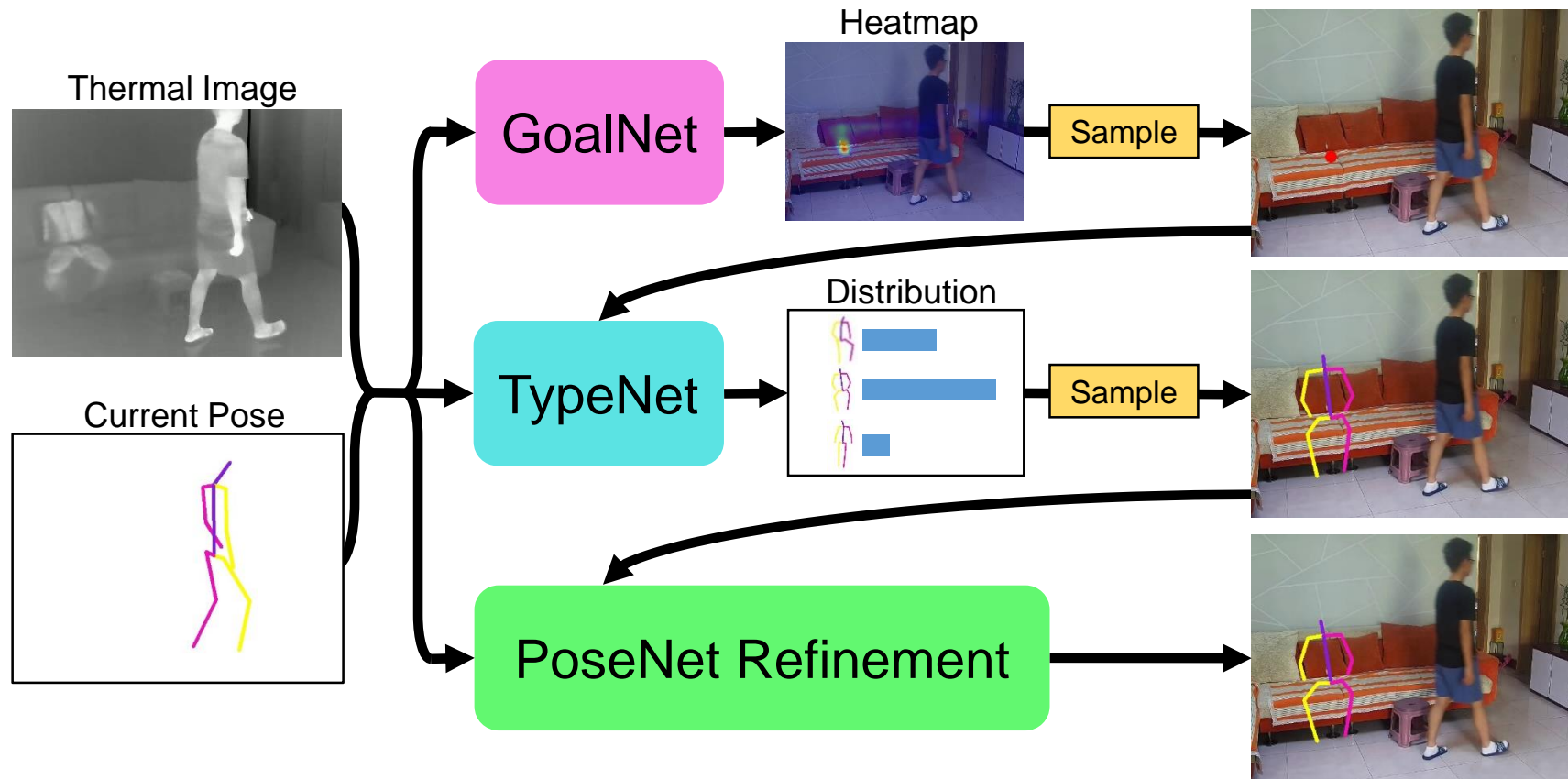


RGB-Thermal and RGB-Depth videos of indoor human motion with estimated human poses.

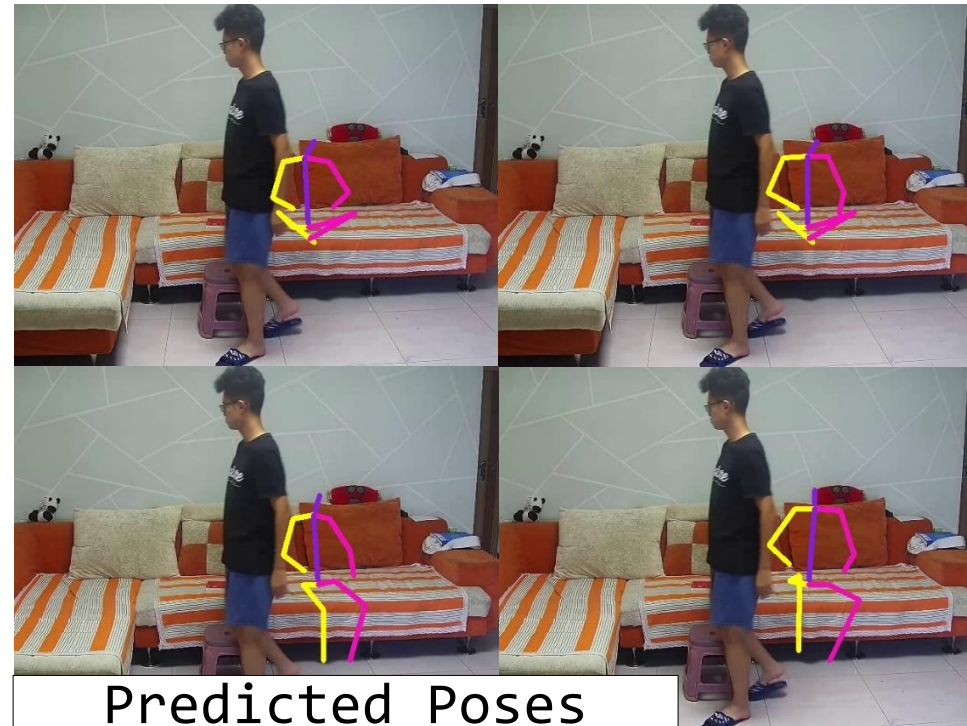
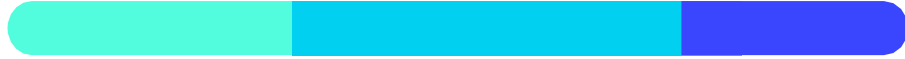
783 video clips, 10.4 hours



# Method



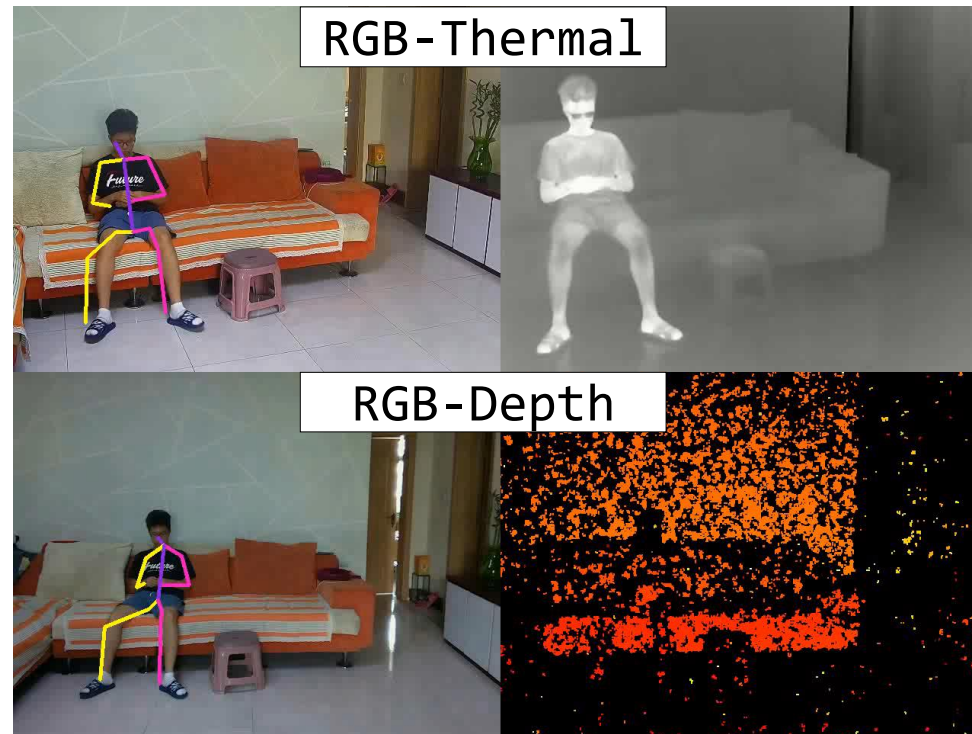
# Results



# Thermal Indoor Motion Dataset



RGB-Thermal and RGB-Depth videos of indoor human motion





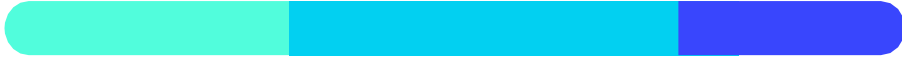
# Thermal Indoor Motion Dataset



2 actors, 3 rooms in multiple view angles



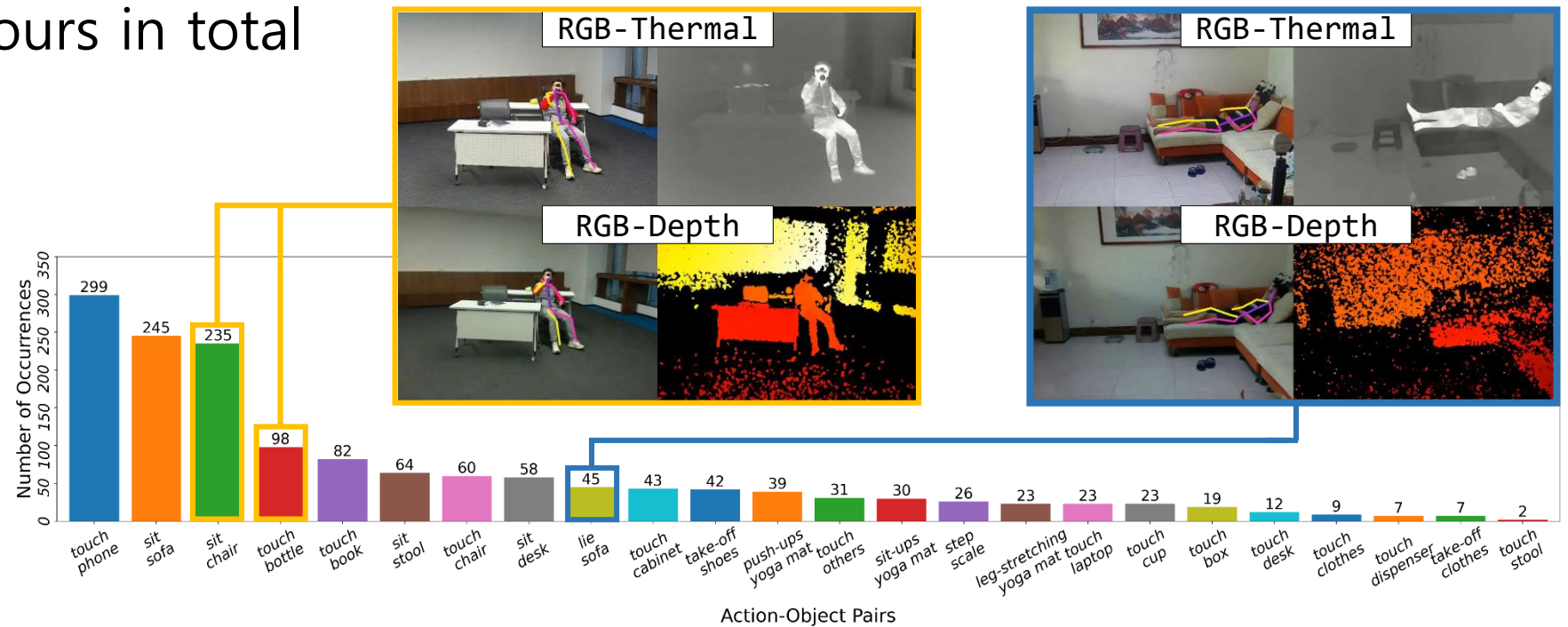
# Thermal Indoor Motion Dataset



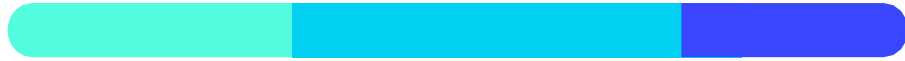
2 actors, 3 rooms in multiple view angles

24 types of actions with annotated start and end time

783 clips, 10.4 hours in total



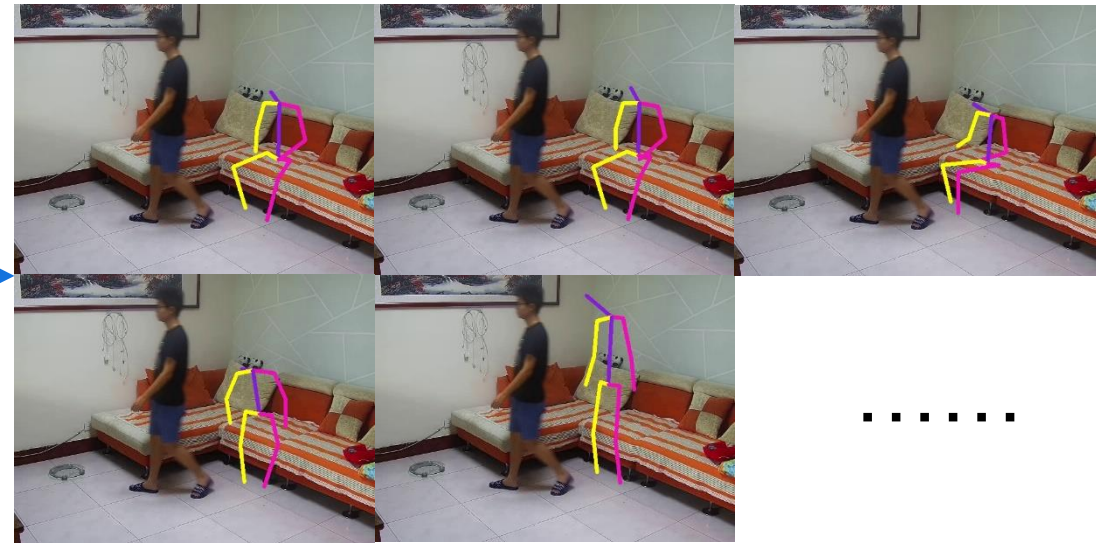
# Past human pose estimation



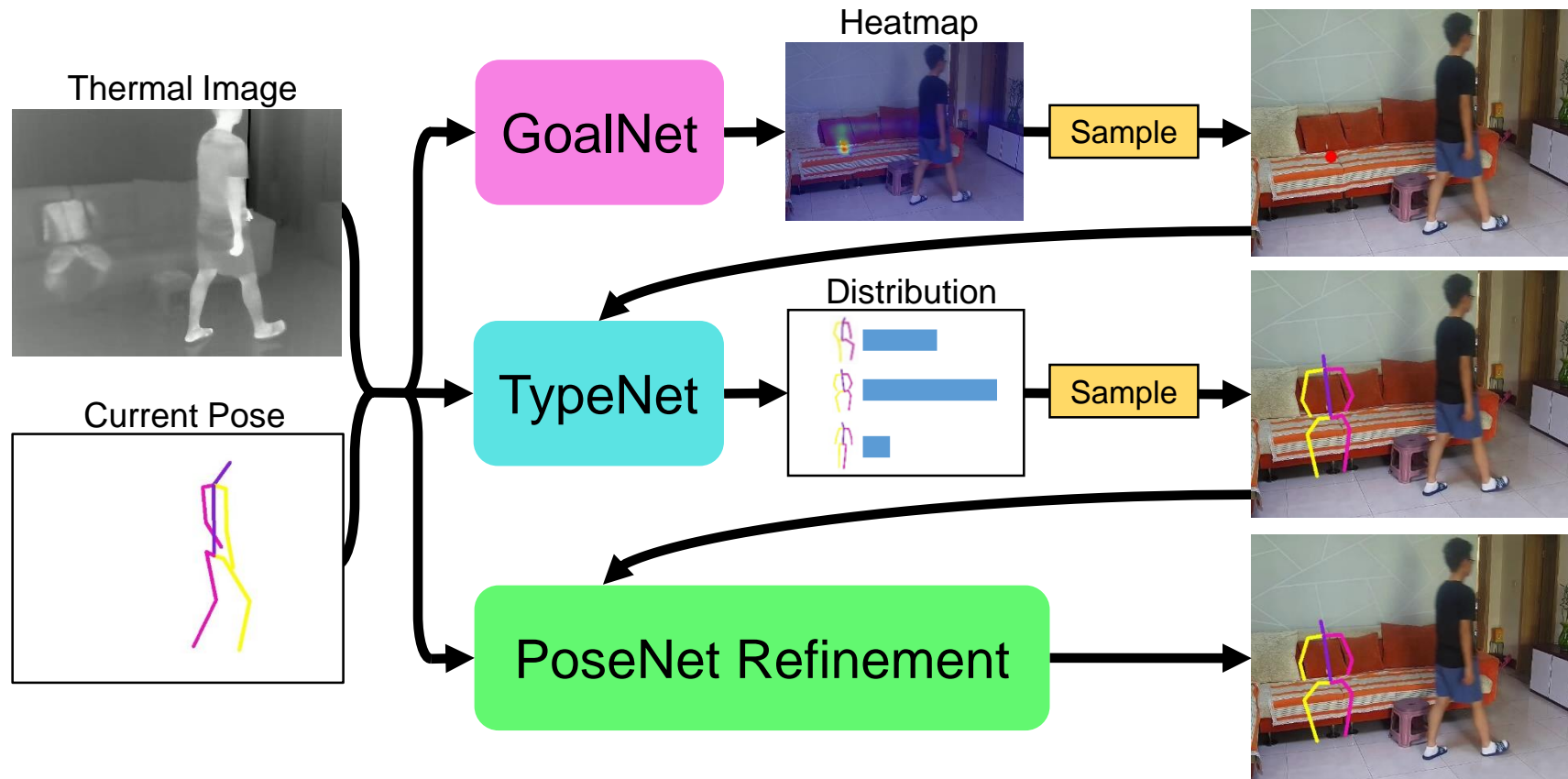
Given an indoor thermal image with a person in it, generates  $M$  ( $= 30$ ) possible poses of the person  $N$  ( $= 3$ ) seconds ago.



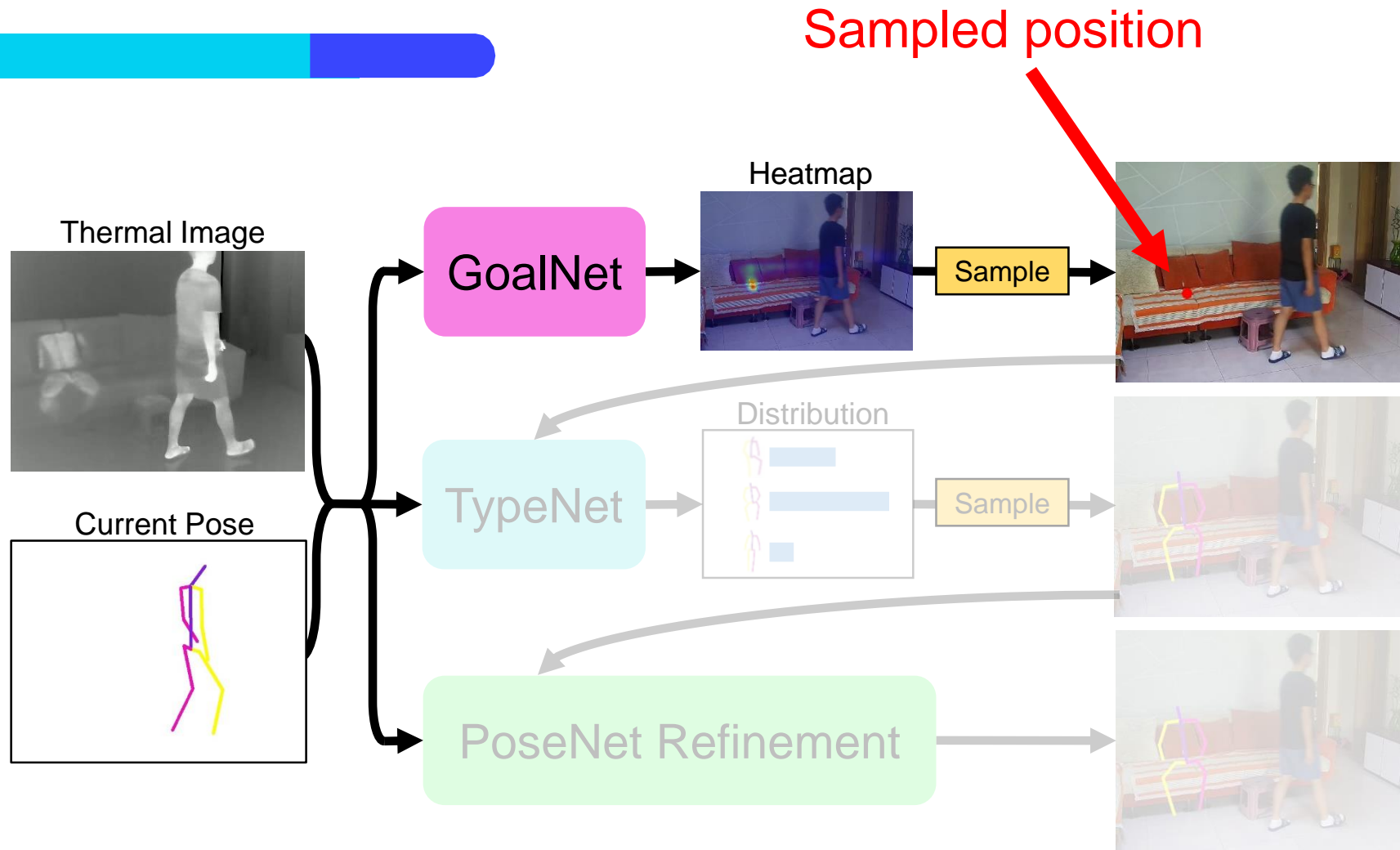
Model



# Method

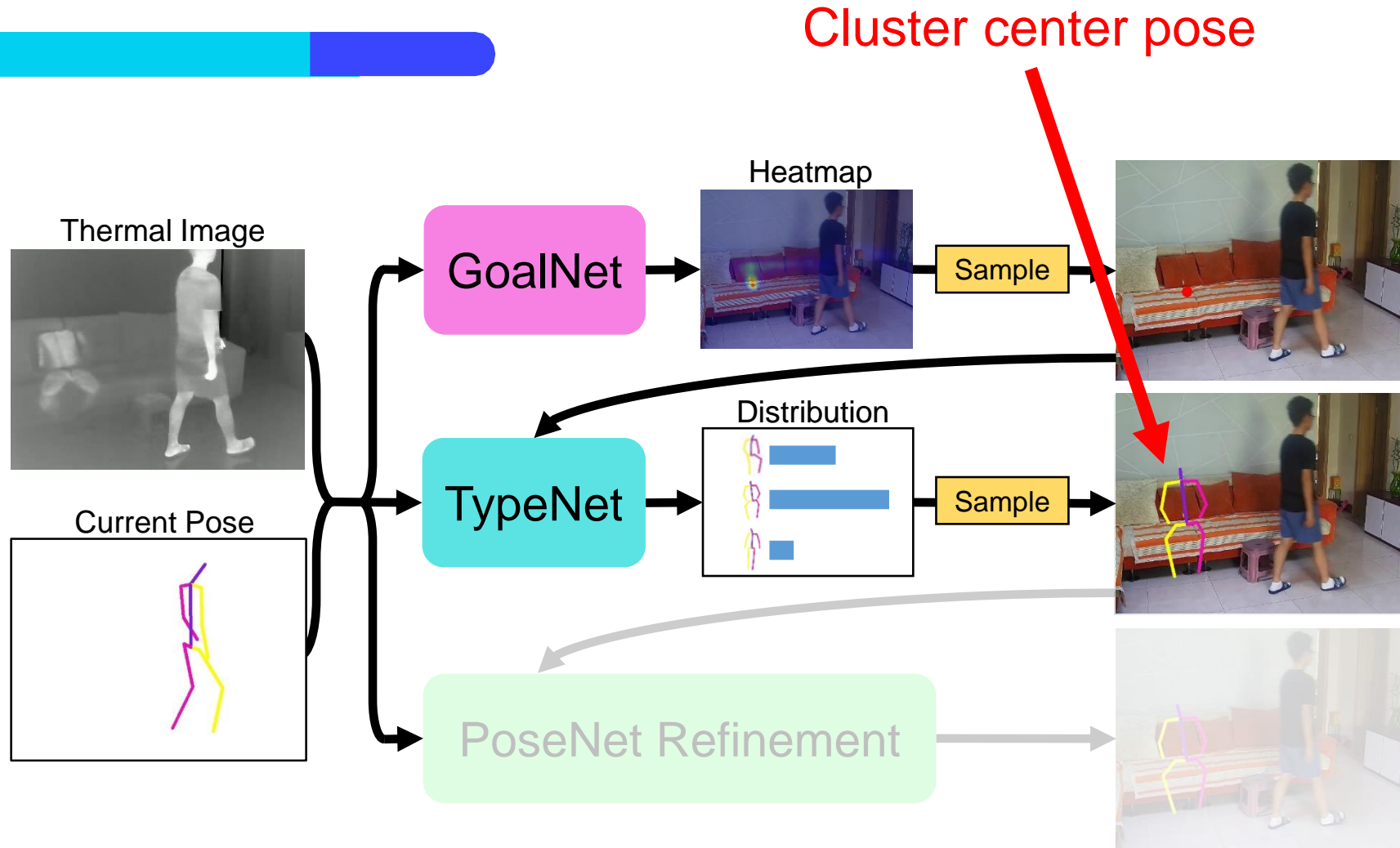
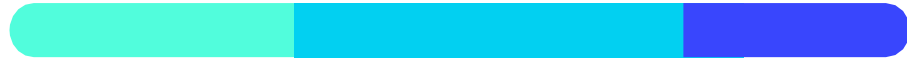


# Method



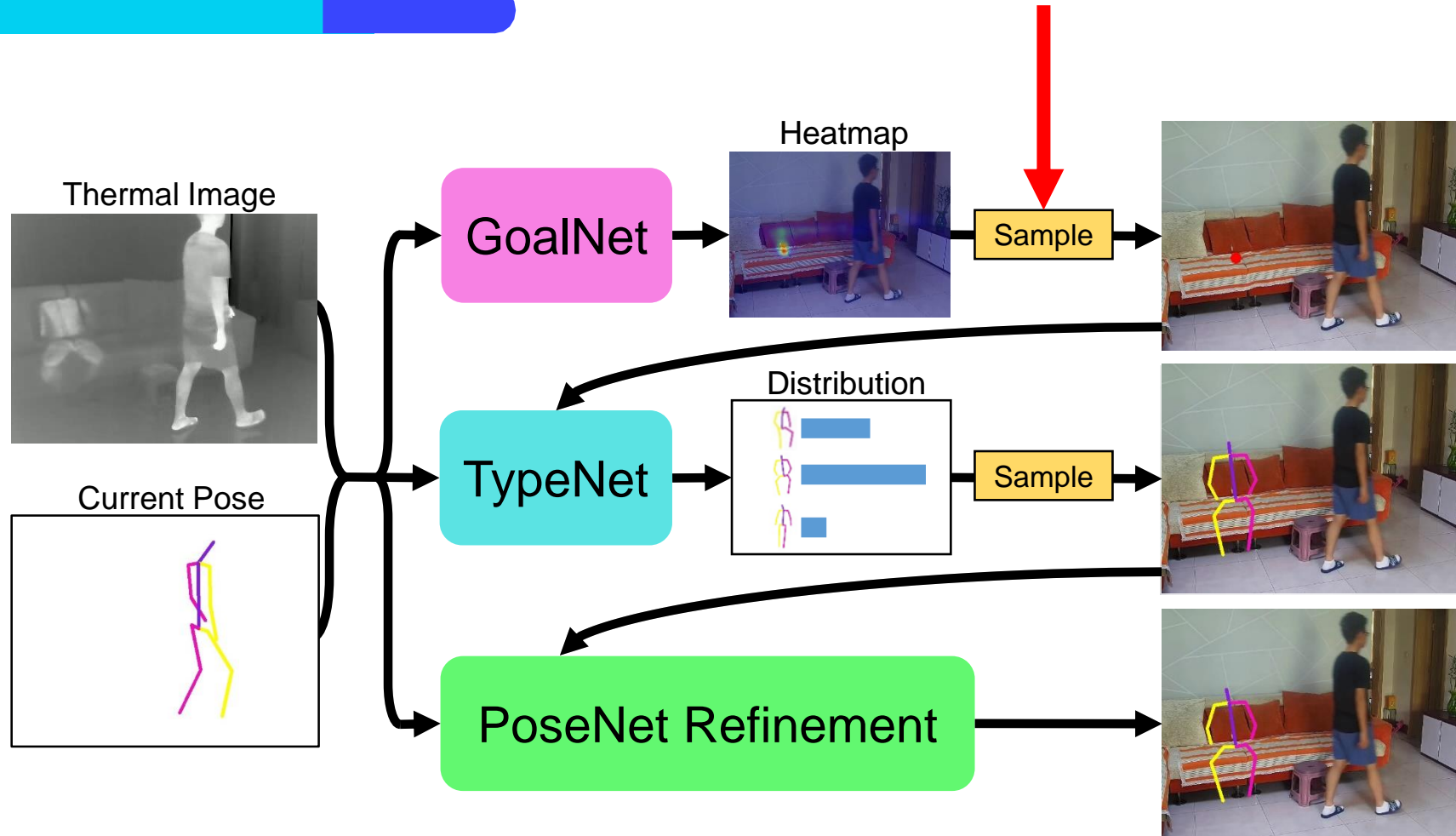


# Method



# Method

Repeat this for multiple answers



# Evaluation metrics



## Mean Per Joint Position Error (MPJPE)

Evaluates the top- $k$  ( $= 1,3,5$ ) generated poses.  
Measures their differences to the ground truth.

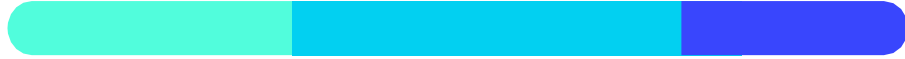
## Negative Log-likelihood (NLL)

Likelihood of the ground truth.

## Semantic Score

The ratio of generated poses that are compatible with the scene affordance.

# Results



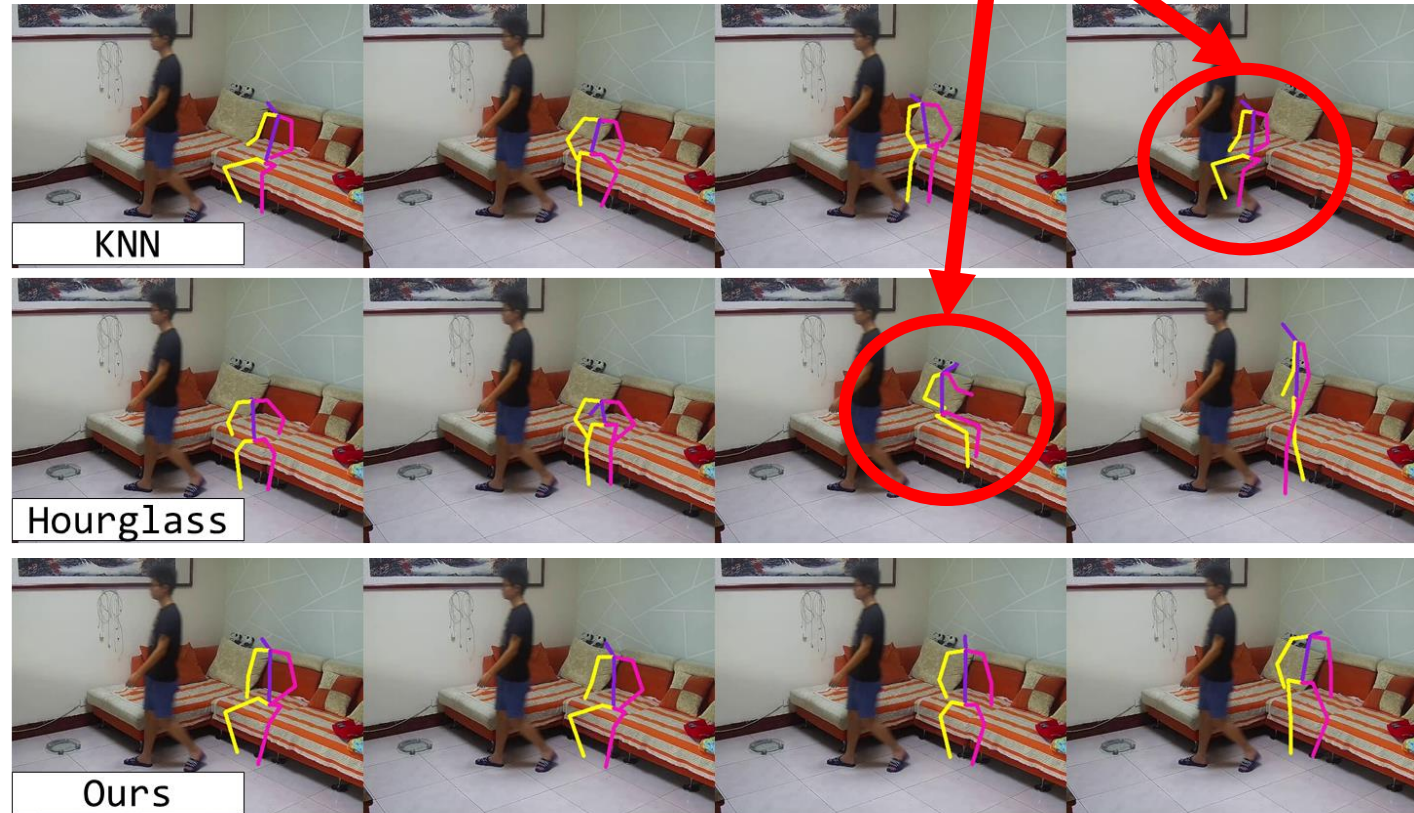
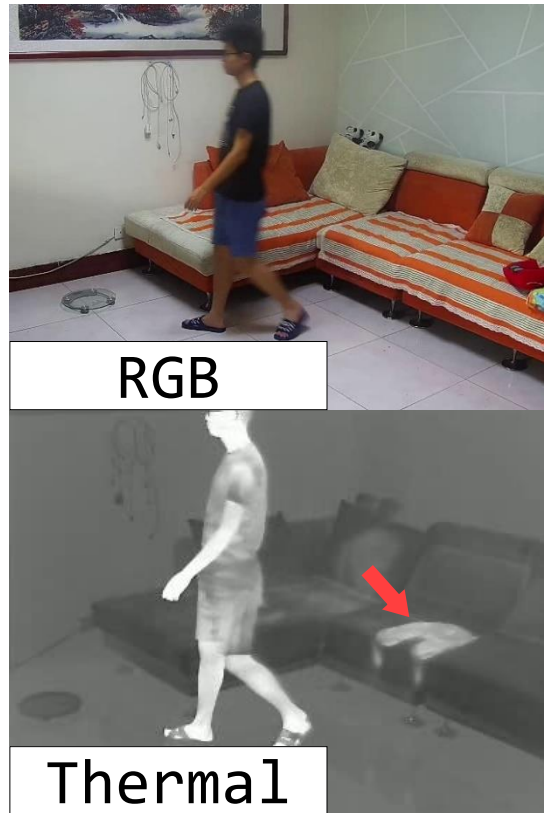
Compare with KNN and one-stage Hourglass baselines

Method	MPJPE			NLL	Semantic Score(%)
	Top 1	Top 3	Top 5		
KNN	19.26	24.53	28.44	N/A	61.94
Hourglass	23.80	27.99	31.03	136.23	67.05
Ours	<b>18.33</b>	<b>22.25</b>	<b>25.25</b>	<b>103.75</b>	<b>82.11</b>

# Results



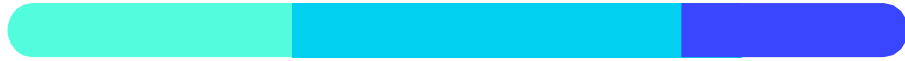
Not compatible with the affordance



All reasonable



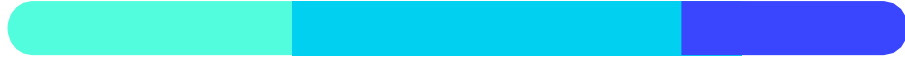
# Results



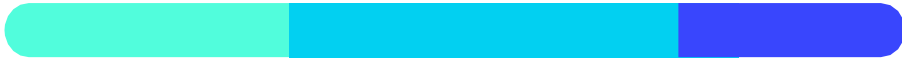
Compare with different input modalities

Input	MPJPE			NLL	Semantic Score(%)
	Top 1	Top 3	Top 5		
RGB	22.06	27.21	31.12	105.03	87.56
Thermal	<b>18.33</b>	<b>22.25</b>	<b>25.25</b>	<b>103.75</b>	82.11
T w/o pose	19.62	24.00	27.27	104.38	80.55

# Results



# Results



Impossible



Not interact with anything

# Results

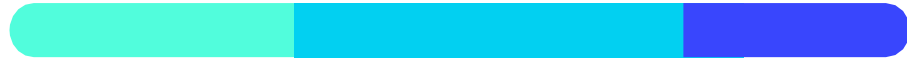


Correlation between thermal mark intensity and time





# Results



Held-out data for generalization test



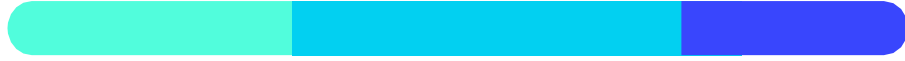


# Results



Changed Factor	Modality	MPJPE			NLL	Semantic Score(%)
		Top 1	Top 3	Top 5		
Arrangement	RGB	21.27	26.38	30.42	107.10	<b>93.69</b>
	Thermal	<b>20.41</b>	<b>25.10</b>	<b>28.36</b>	<b>105.37</b>	89.56
Background	RGB	25.07	30.02	33.47	111.67	<b>83.80</b>
	Thermal	<b>19.85</b>	<b>24.24</b>	<b>27.83</b>	<b>107.82</b>	81.49
Actor	RGB	<b>24.37</b>	29.20	32.77	114.87	<b>91.21</b>
	Thermal	24.60	<b>28.92</b>	<b>31.98</b>	<b>114.26</b>	81.33
Room	RGB	35.05	42.00	47.11	121.14	19.55
	Thermal	<b>23.05</b>	<b>27.59</b>	<b>31.16</b>	<b>112.84</b>	<b>36.88</b>

# Conclusion



A novel task: past human pose estimation with thermal images

Thermal-IM dataset: RGB-Thermal-Depth videos about indoor human motion

A model tackling the task

- Outperforms the baselines

- Thermal imaging makes the problem easy

- Thermal model generalizes well across environment's appearance

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