


Apprentissage de modalités auxiliaires pour la localisation basée vision

Enhancing Visual-Based Localization by Learning Appearance of Paired Modalities

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Introduction

Related work

Our proposal: Learning side information with modality transfer

Experiments

Conclusion

Introduction

Visual Based Localization

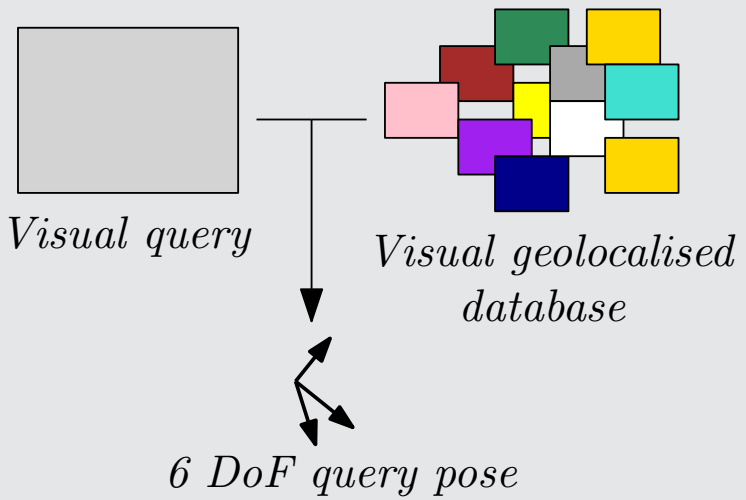
Visual Based Localization (**VBL**) aims to recover the pose or position of a visual input query according to a known visual reference.

$\rightarrow$ **?** $\rightarrow$

Direct vs Indirect methods

Visual Based Localization (**VBL**) methods can be devided in two mains categories [Piasco et al., 2017]:

Direct methods



- Accurate
- Position + orientation
- Small area

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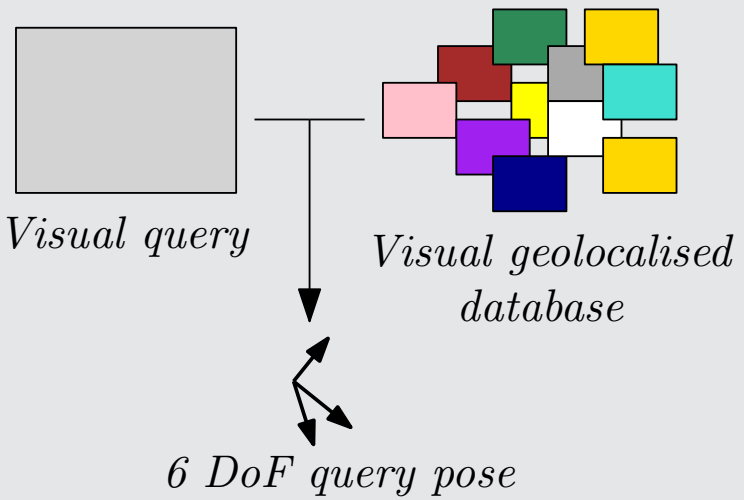

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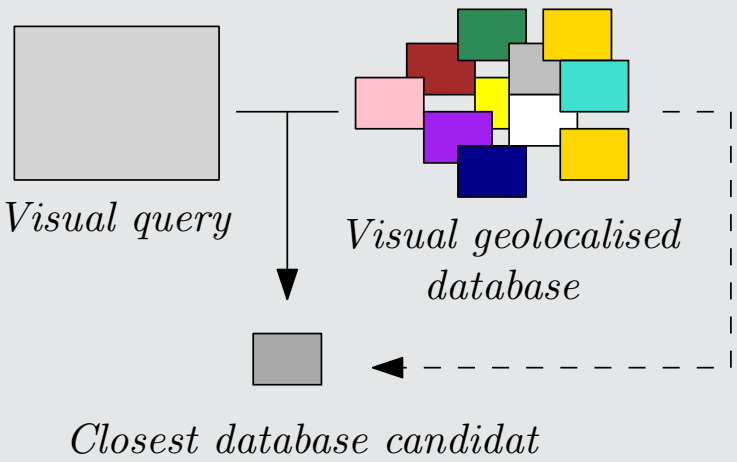
Indirect methods



- Coarse position
- Cover large are
- Fast

Visual Based Localization: Indirect methods

VBL can be solved by retrieving the closest geo-referenced candidate in the database.

→

26.45 04.52

14.12 05.05

27.55 03.99

18.50 02.99

19.13 07.18

28.19 01.12

27.69 03.80

Visual Based Localization: Indirect methods

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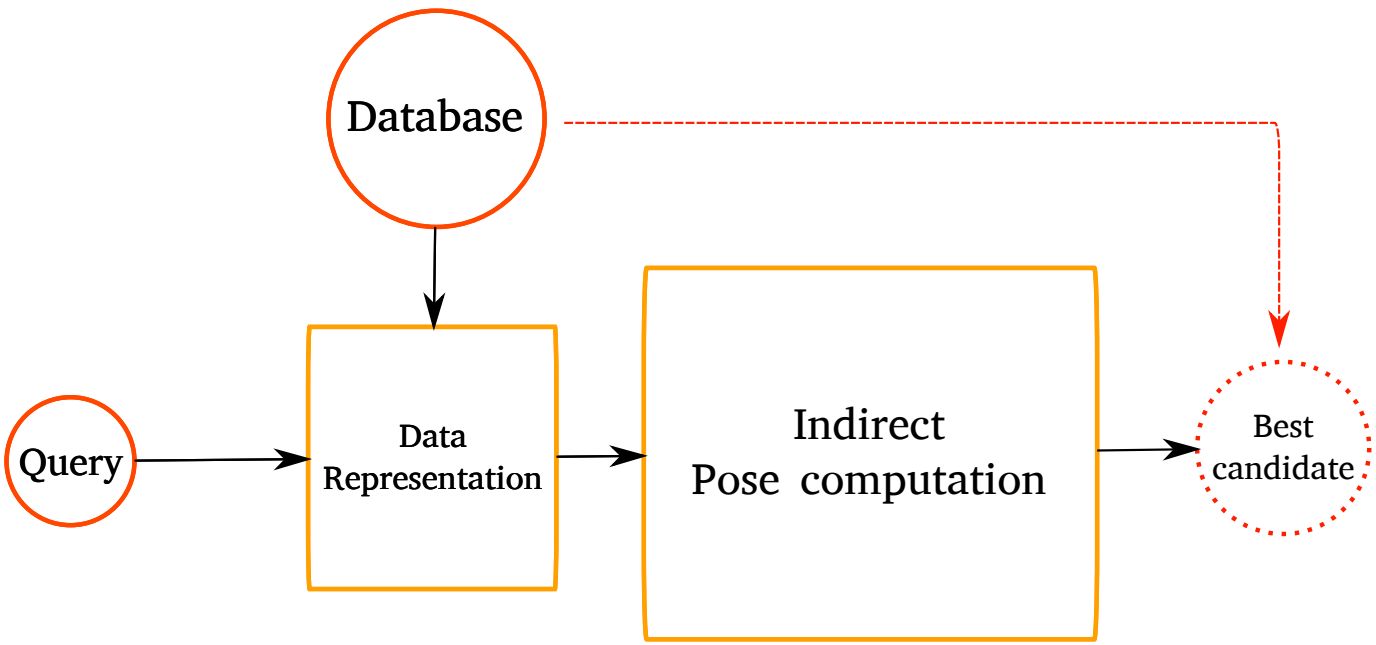
Indirect methods: Pipeline

We propose a new data representation for solving indirect VBL.



Various modalities

In this work, we tackle the problem of VBL with **not only** images.

Modalities that could be used

- **Image** (main modality)

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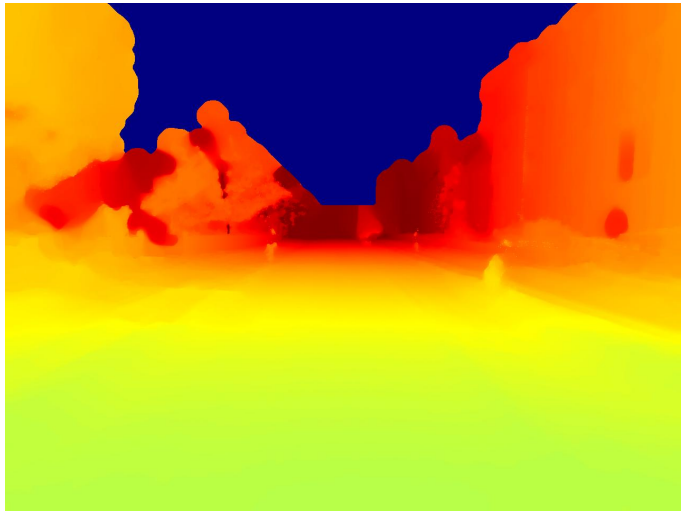

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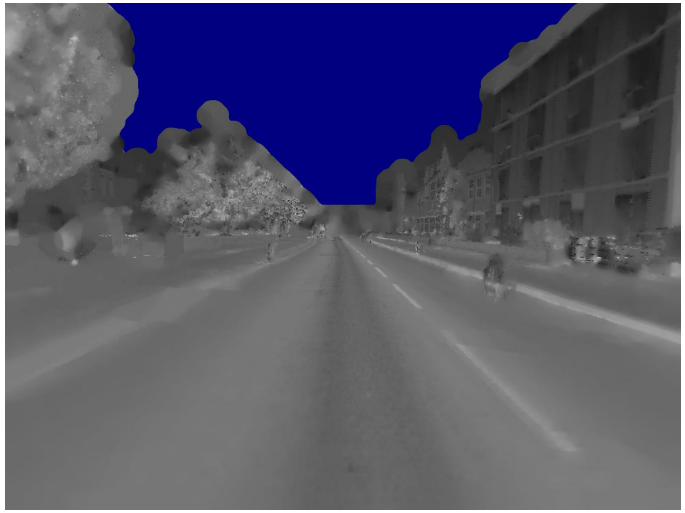
Modalities that could be used

- **Image** (main modality)
- Depth map
- Reflectance



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Modalities that could be used

- **Image** (main modality)
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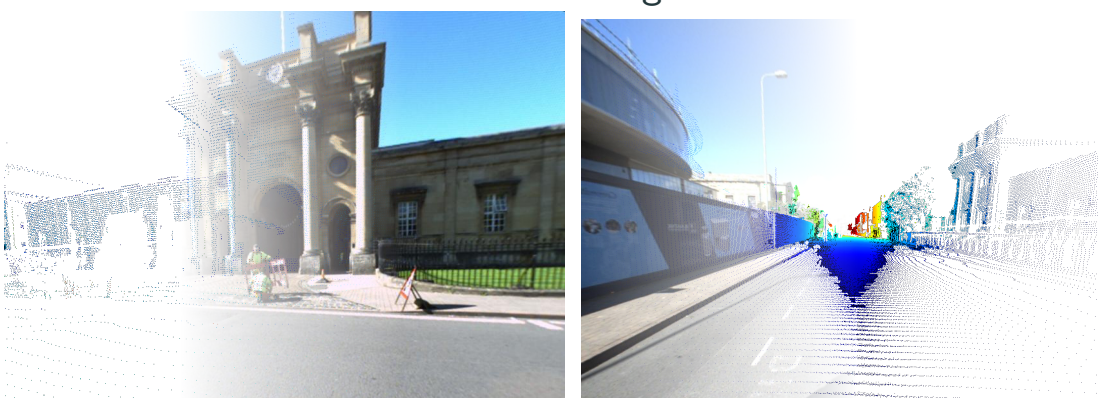
- Reflectance
- Semantic information
- ...

Heterogeneous modalities

Available data

Training data type	Testing data type
RGB + Depth	RGB

Multi-modal training dataset



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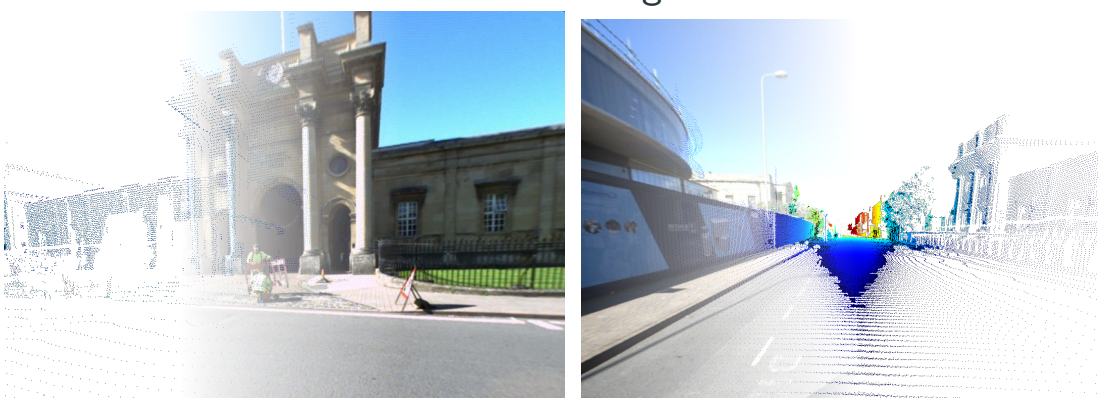
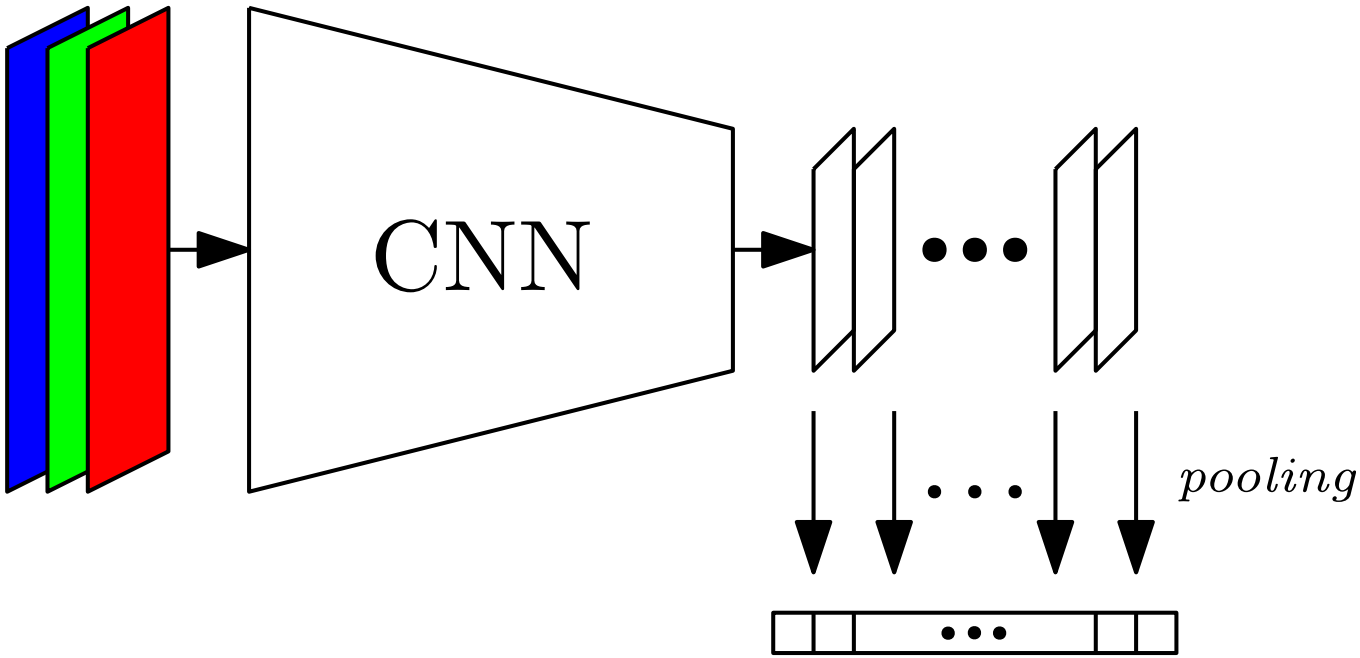


Single modality data at test time

Related work

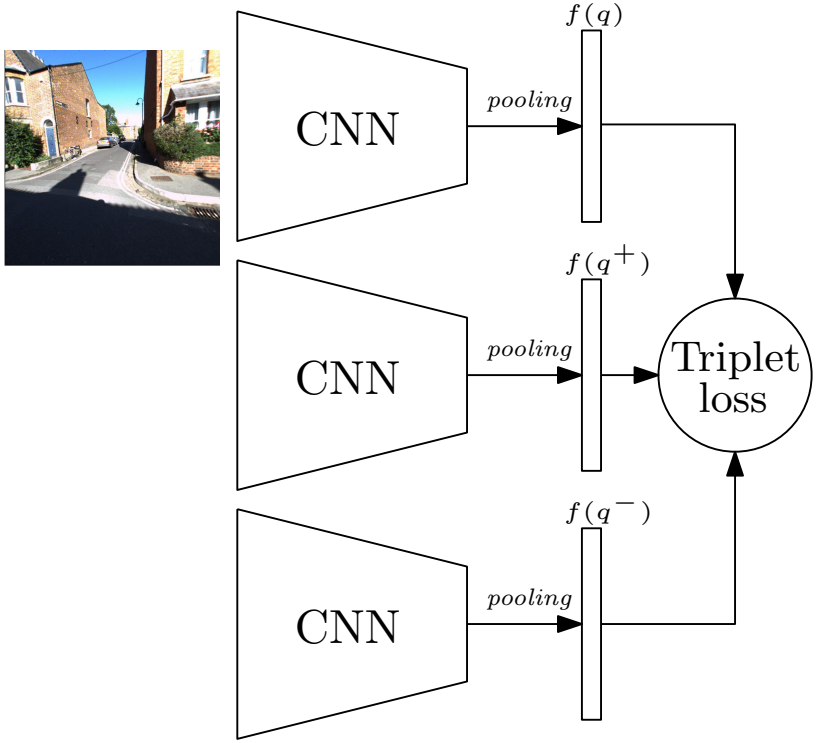
Building a deep image descriptor

Fully connected part of the network is dropped and pooling is done on the last convolutional response:



More complex aggregation methods exist:
NetVLAD [Arandjelović et al., 2017], RMAC [Radenović et al., 2016]...

Learning a deep image descriptor



$$Loss_{triplet} = max\left(\left\|f(q) - f(q^+)\right\|^2 - \left\|f(q) - f(q^-)\right\|^2 + \lambda, 0\right), \quad (1)$$

$$with \begin{cases} f(x) = \text{descriptor of image } x \\ \lambda = \text{triplet loss margin} \\ q = \text{query image} \\ q^+ = \text{positif example} \\ q^- = \text{negatif example} \end{cases}$$

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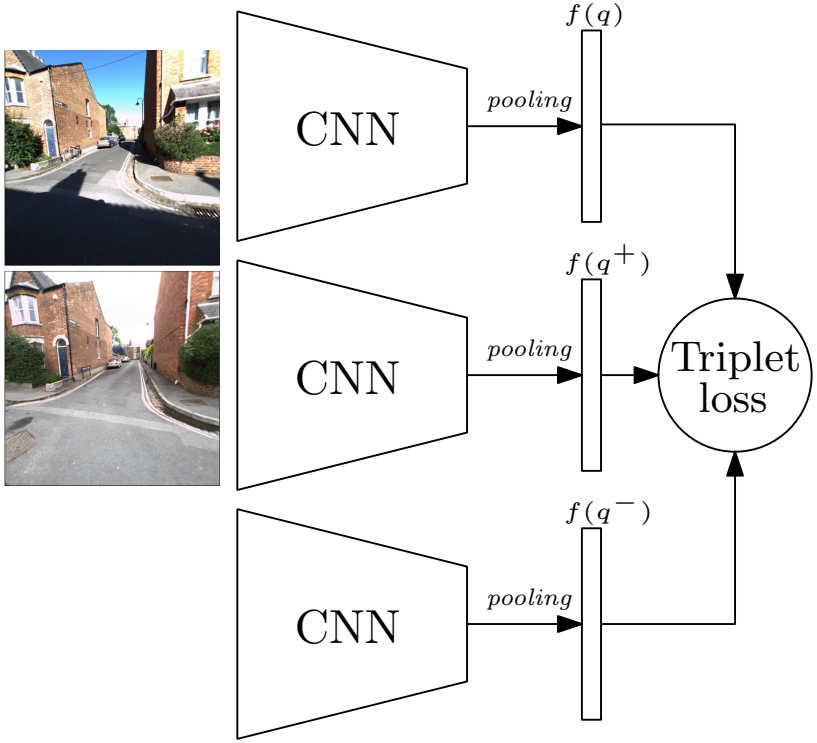

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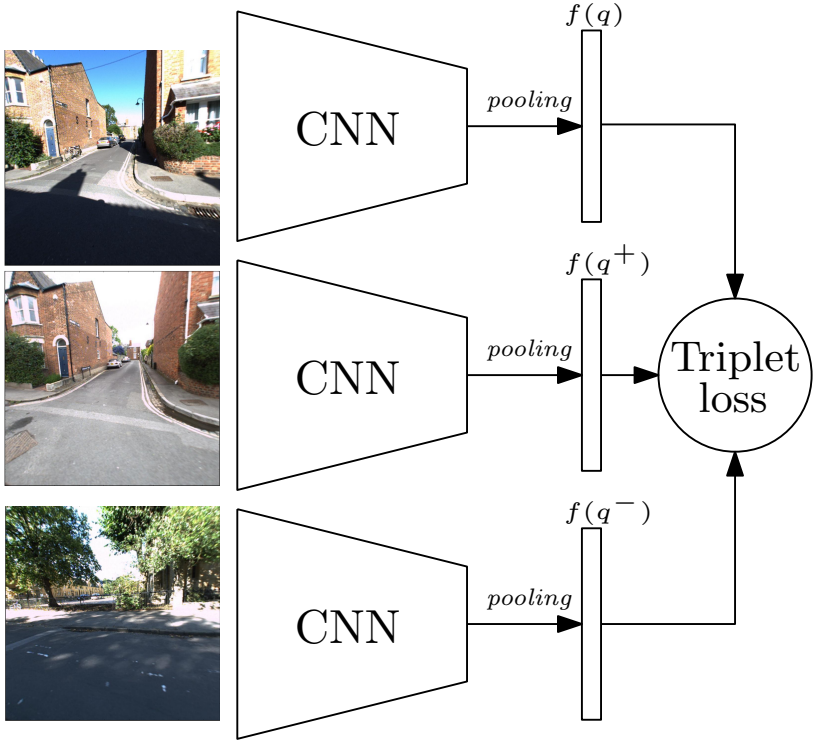

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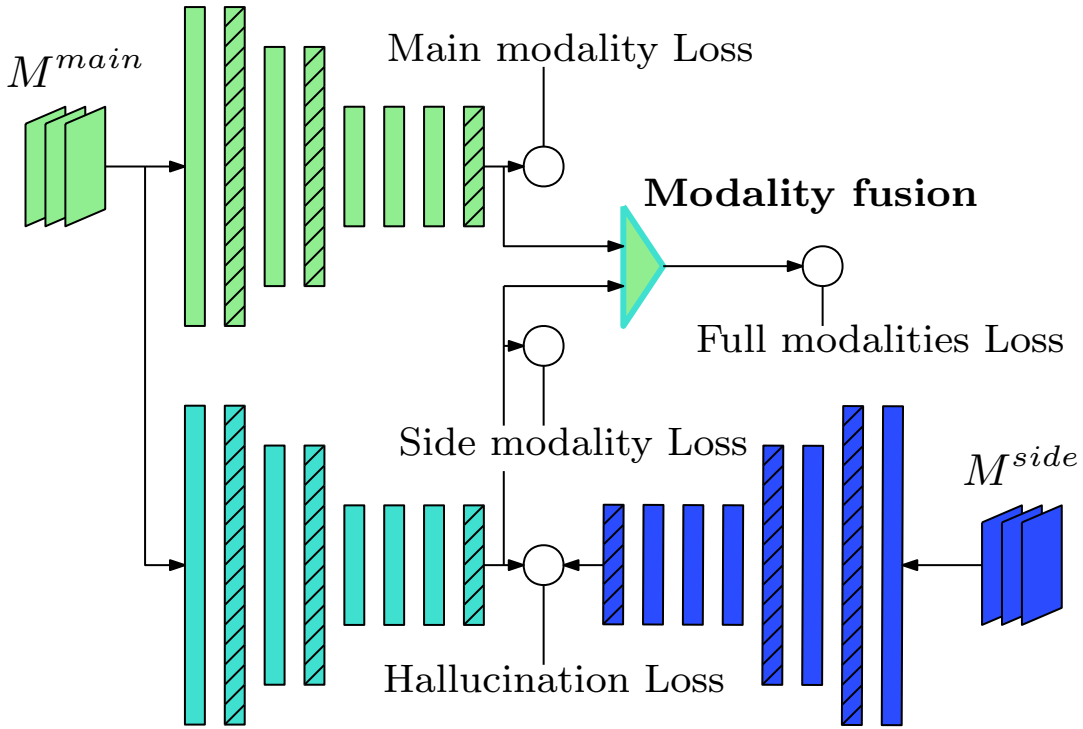
Learning with side modality

Hallucination architecture from [Hoffman et al., 2016] for objects classification, **never applied to image description and VBL**.



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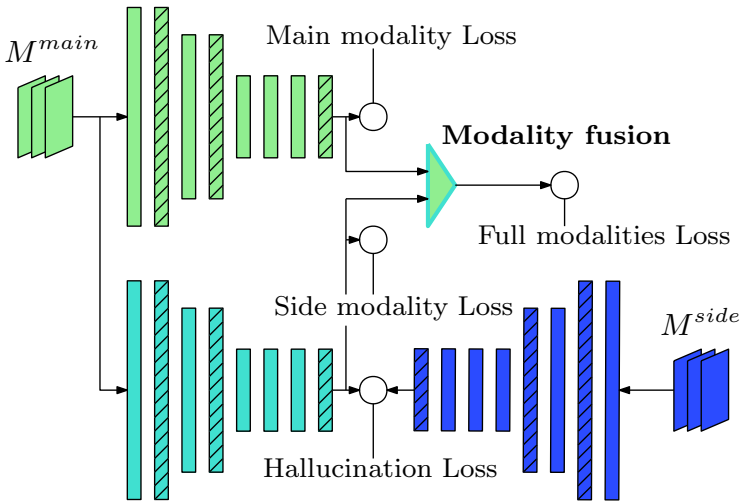
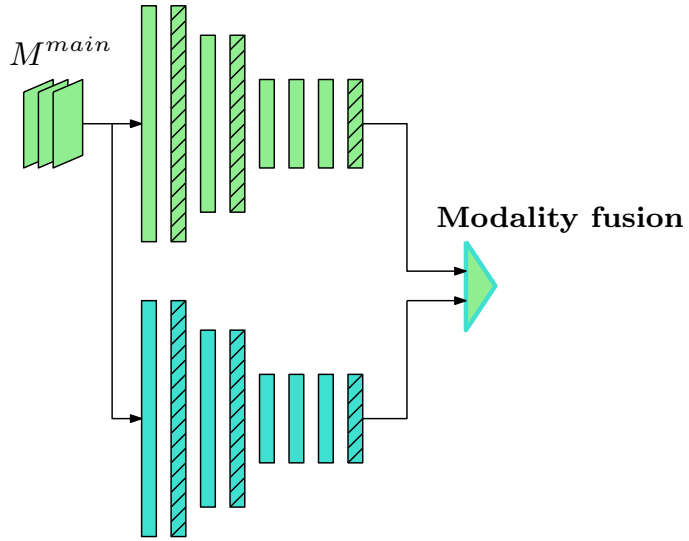




Deployment

Our proposal: Learning side information with modality transfer

Intuition

Current encoder-decoder network architecture currently outperforms all other methods for **modality transfer**.

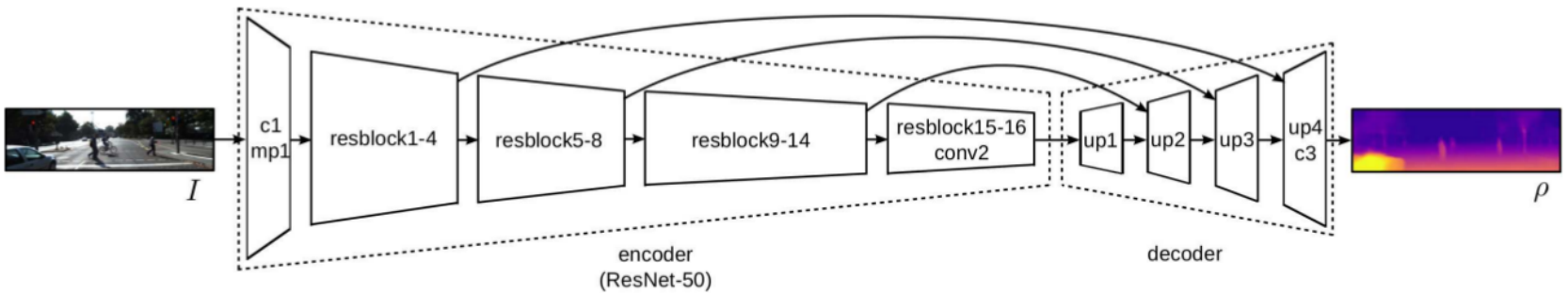
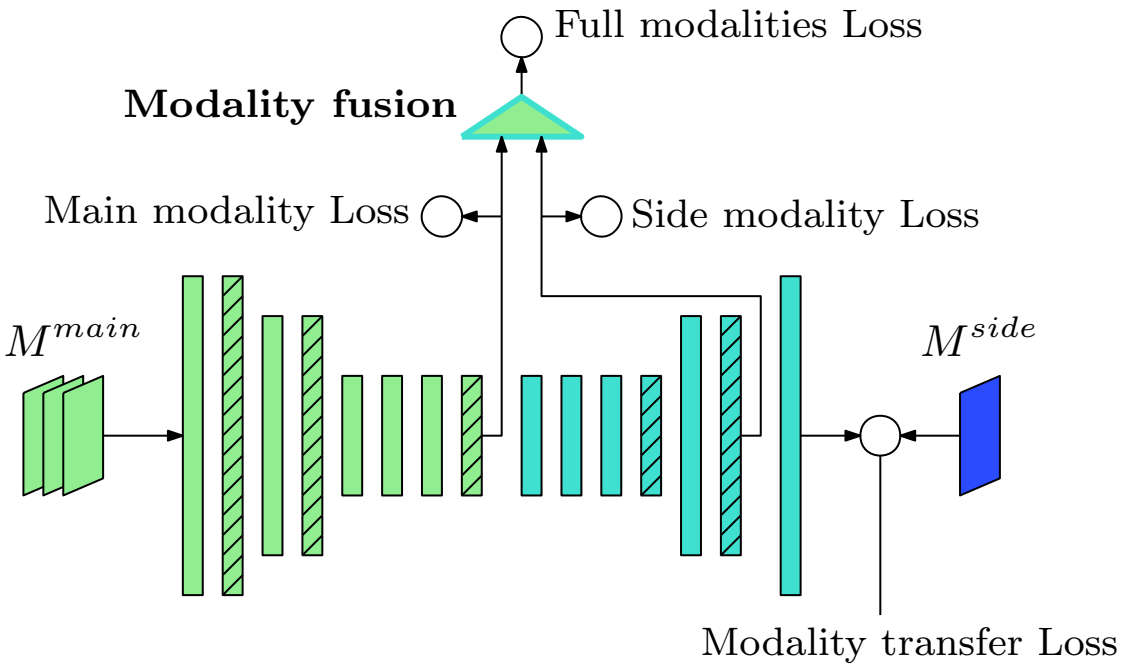


Illustration from [Kuznietsov et al., 2017]

Proposed architecture

The proposed architecture is inspired by encoder-decoder networks:



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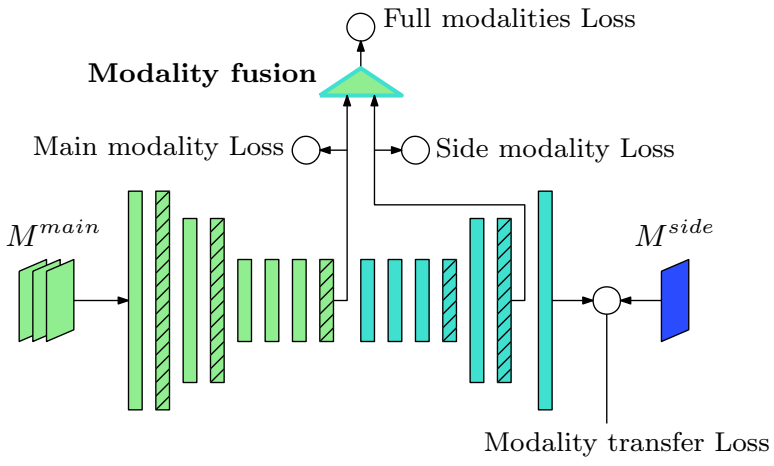

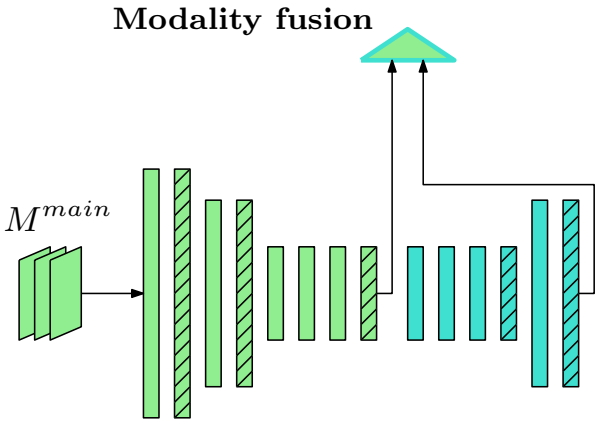

Deployment

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$$Loss_{transfer} = \left\| \widetilde{M}(M^{main}) - M^{side} \right\|_1, \tag{2}$$

where $\widetilde{M}(x)$ denotes the output of the decoder part of the network regarding input x.

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$$Loss = Loss^{main}_{triplet} + Loss^{side}_{triplet} * \sigma_{side} + Loss^{full}_{triplet} * \sigma_{full} + Loss_{transfer} * \sigma_{transfer}. \tag{3}$$

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Diversification loss:

$$Loss_{div} = max\left(Loss^{full}_{triplet} - Loss^{main}_{triplet} + \lambda_{div}, 0\right), \tag{4}$$

where λ_{div} is a scalar value that acts as a margin to ensure $Loss^{full}_{triplet}$ is always smaller than $Loss^{main}_{triplet}$.

Advantages over hallucination

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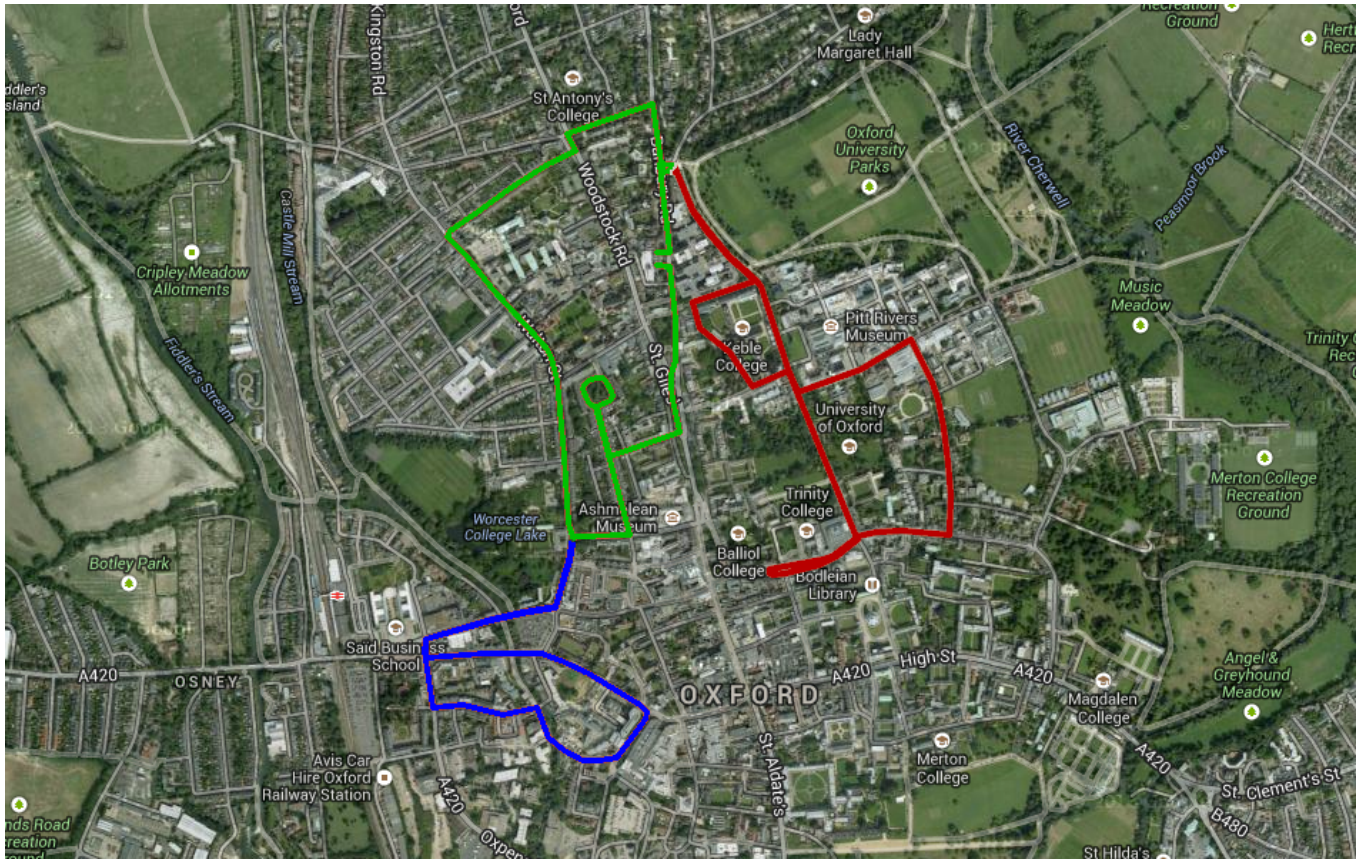
- No need of pretraining on side modality
- Method by nature lighter: $29k$ parameters vs. $41k$ parameters for networks built upon Alexnet architecture
- No need to transform modality into 3 channels data

Experiments

Robotcar dataset



Dataset training (green), validation (blue) and testing (red) areas.

Robotcar dataset

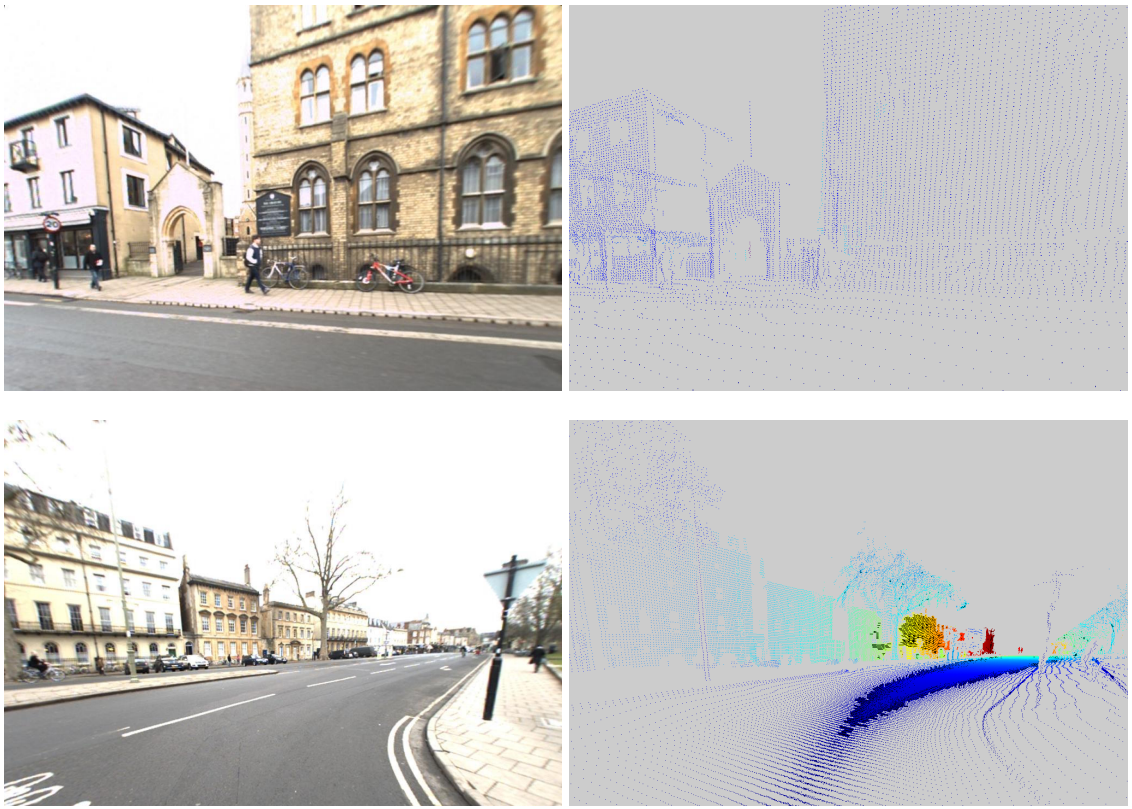
Query

Closest example in the database

Examples of queries with corresponding dataset candidates of the testing set.

Building dense modality map

Image **Points cloud**



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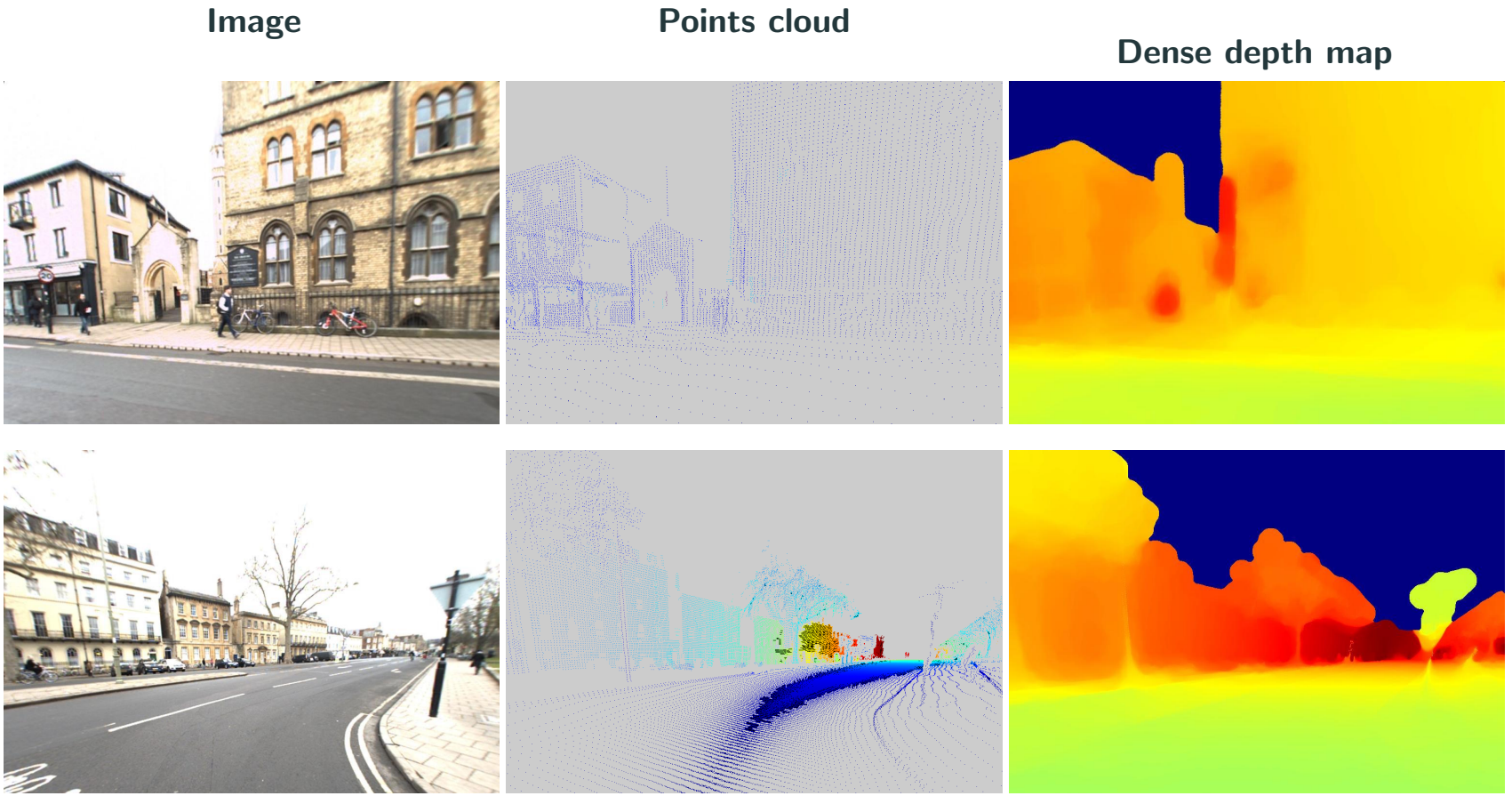

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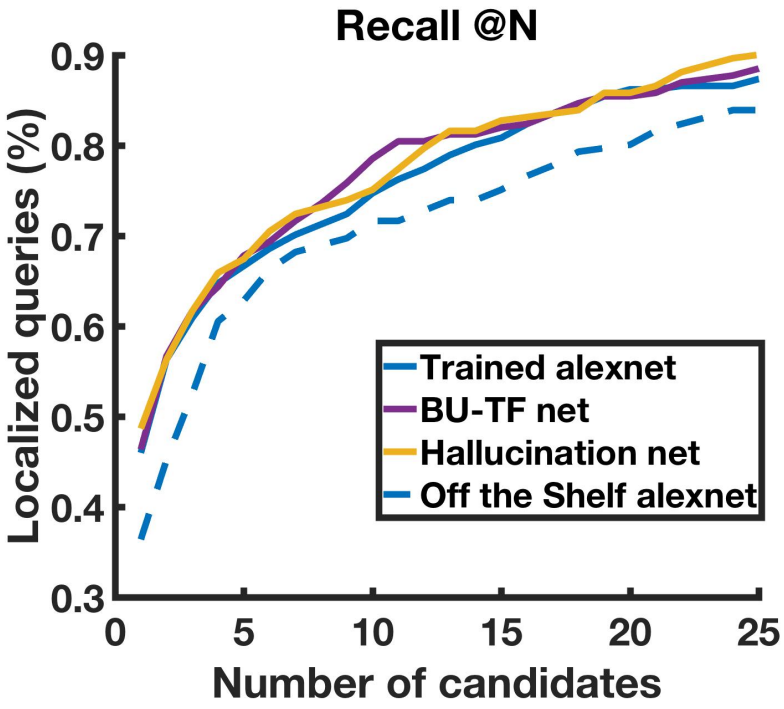
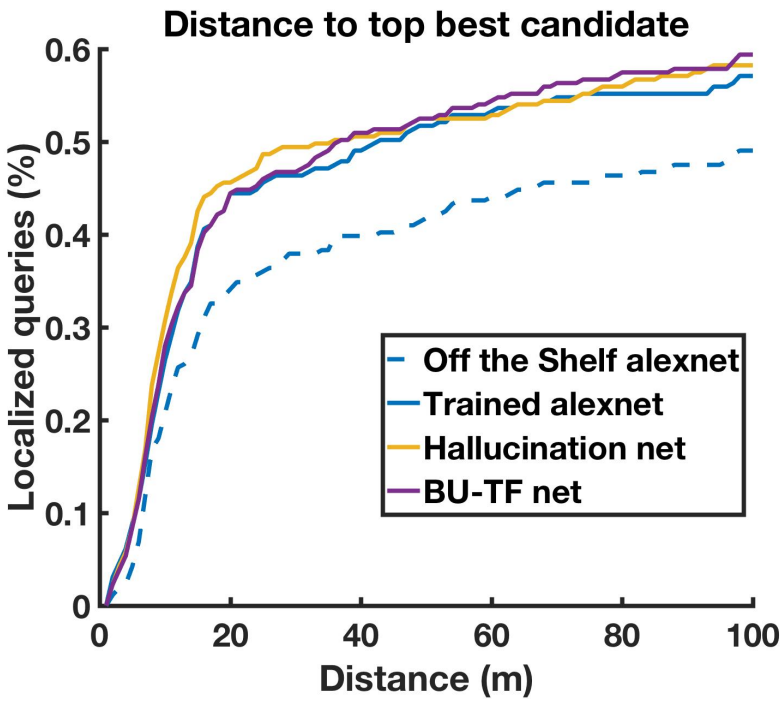
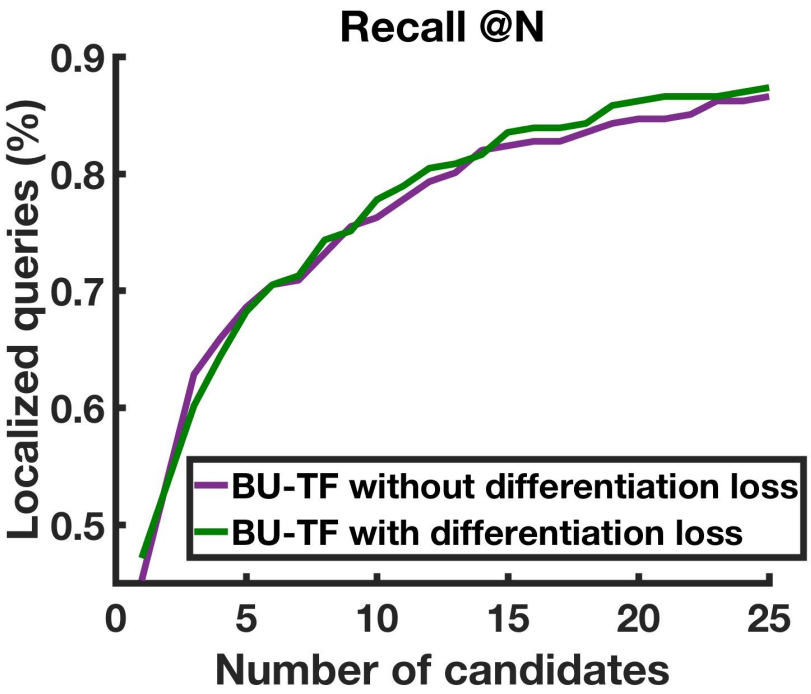
Results

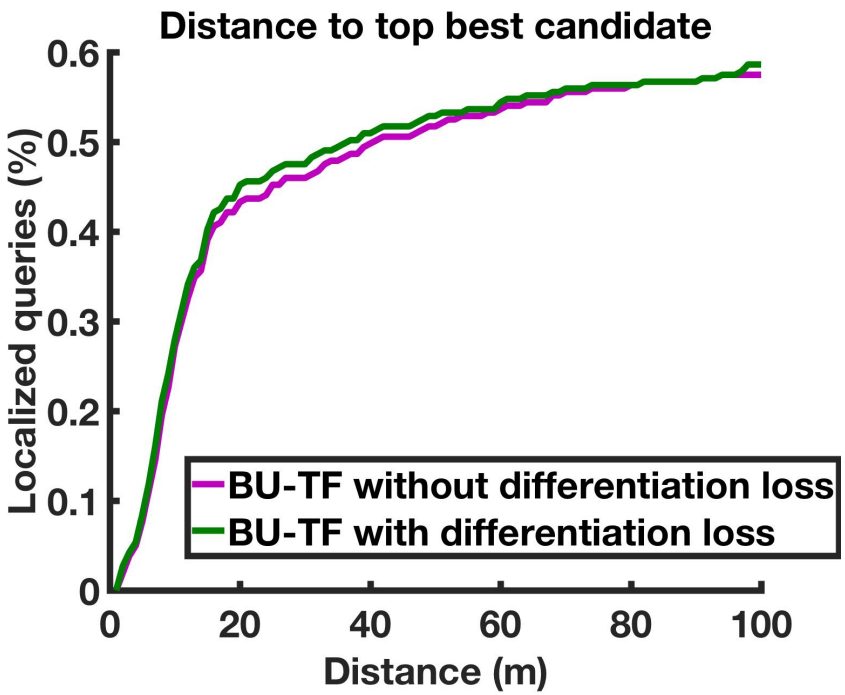




Off-the-shelf: network only trained on ImageNet, no fine-tuning for this specific task and on these specific data.

Results - Diversification loss



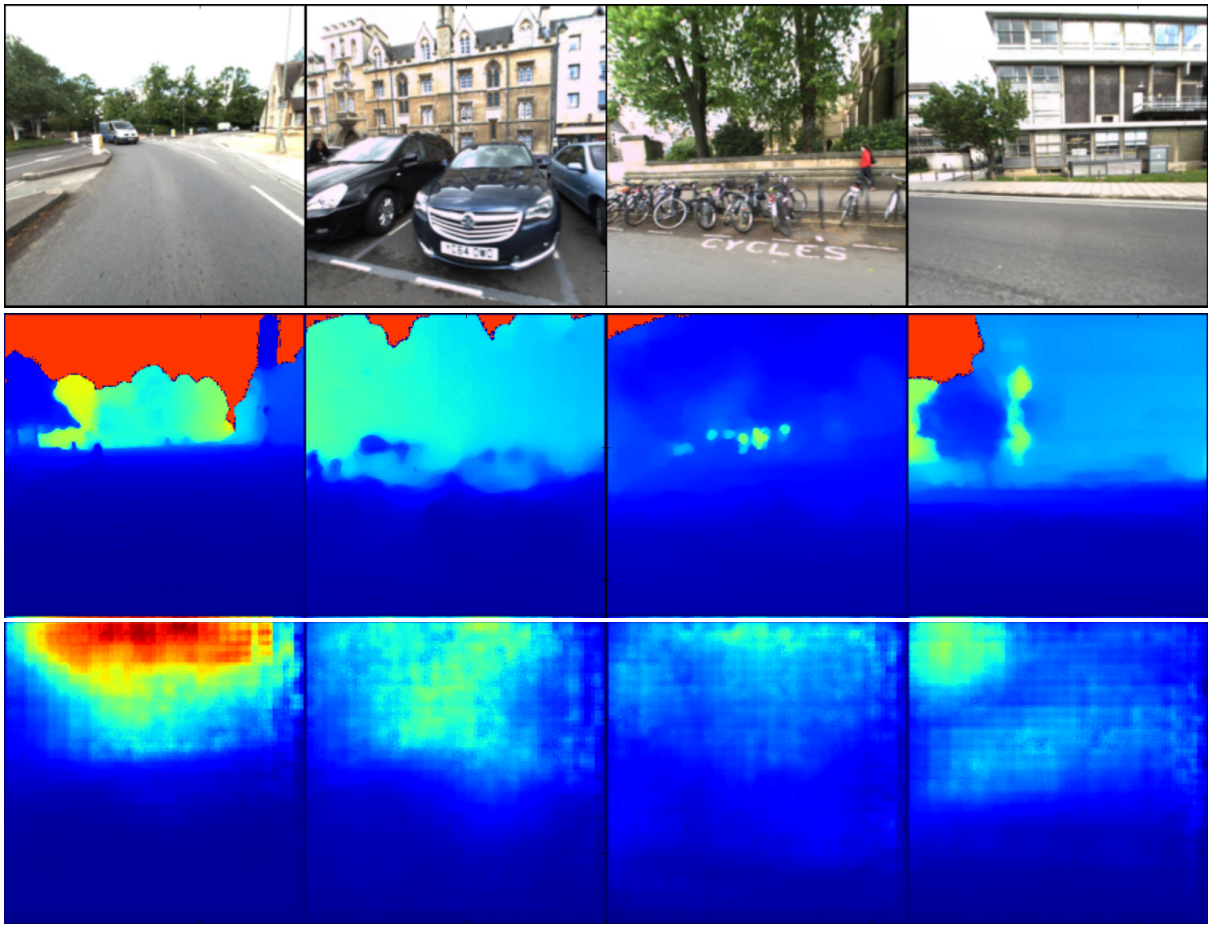


Results - Visual inspection

Main modality

Ground truth side modality

Reconstructed side modality



Results - Conclusion

Comparison with state of the art method:

	Improvement over images-only method	Size	Training steps
Hallucination [Hoffman et al., 2016]			
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Results - Conclusion

Comparison with state of the art method:

	Improvement over images-only method	Size	Training steps
Hallucination [Hoffman et al., 2016]	**Yes**	2x	3 steps
BU-TF (Our proposal)	**Yes**	**1.4x**	**2 steps**

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Future work – The presented method has to be tested:

- on other modalities
- with other aggregation scheme
- on other visual localisation tasks (*e.g.* pose regression)

Thanks for your attention

Question time

References I


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