



# Apprentissage de modalités auxiliaires pour la localisation basée vision

Enhancing Visual-Based Localization by Learning Appearance of Paired Modalities

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Nathan Piasco

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Congrès Reconnaissance des Formes, Image, Apprentissage et Perception 2018

Introduction

Related work

Learning side information with modality transfer

Experiments

Conclusion

## **Introduction**

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# Visual Based Localization

Visual Based Localization (**VBL**) aims to recover the pose or position of a visual input query according to a known reference [Piasco et al., 2017].

Graph illustration VBL: Query → ? → Map



Introduction



# Visual Based Localization: Indirect methods

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

Graph illustration VBL: Query → Geo-taged images → Map



# Visual Based Localization: Indirect methods

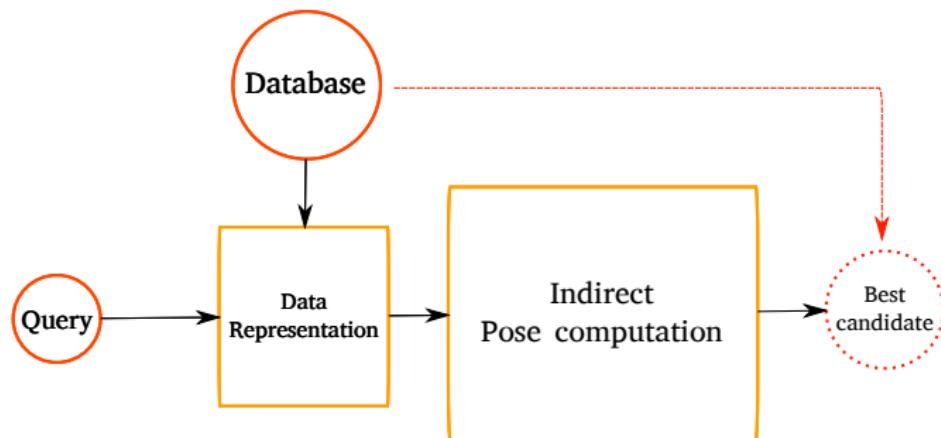
VBL can be solved by retrieving the closest geo-referenced candidate in the database.

Graph illustration VBL: Query → Closest Geo-taged image → Map location



## Indirect methods: Pipeline

We propose a new data representation for solving indirect VBL.



# Heterogeneous modalities

## Available data

Training data type	Testing data type
RGB + Depth	RGB

Multi-modal training dataset

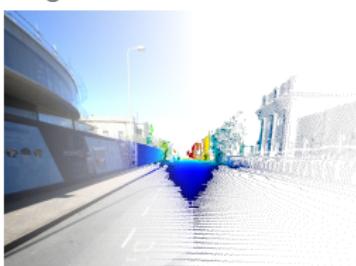


# Heterogeneous modalities

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Single modality data at test



# Heterogeneous modalities

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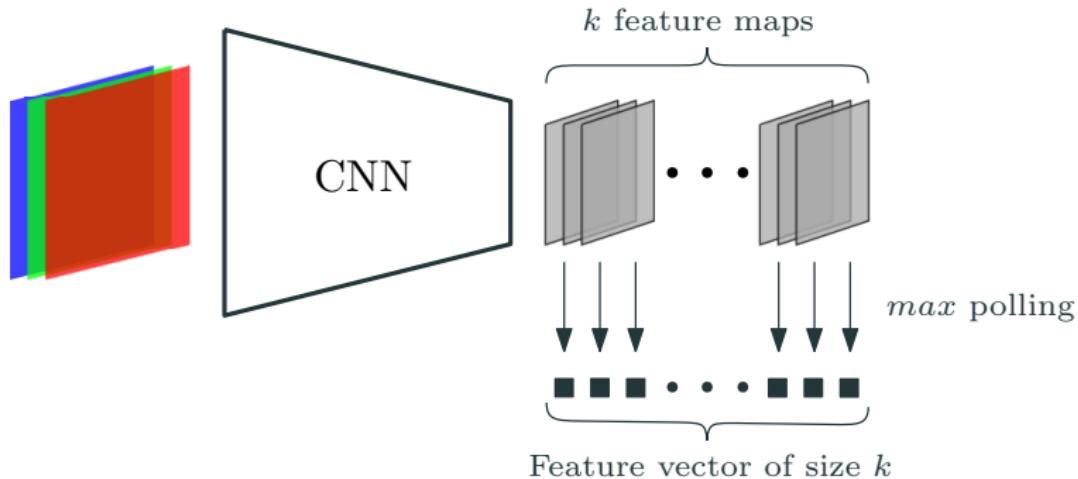


## Related work

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# Building a deep image descriptor

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



More complex aggregation methods exist:

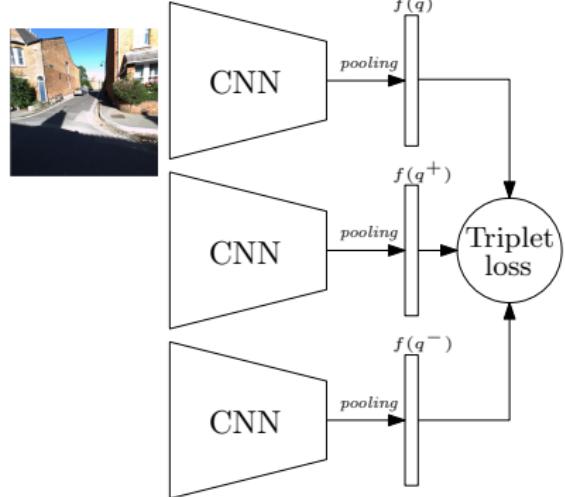
NetVLAD [Arandjelović et al., 2017], RMAC...



Related work



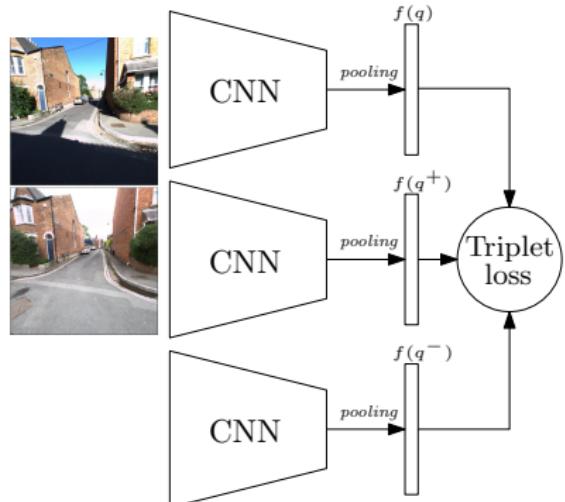
# Learning a deep image descriptor



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

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

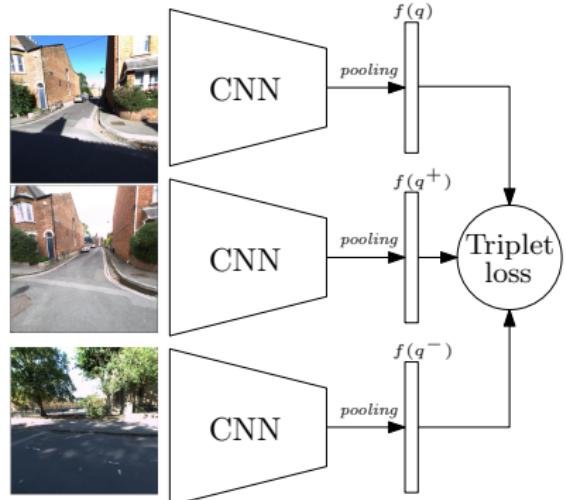
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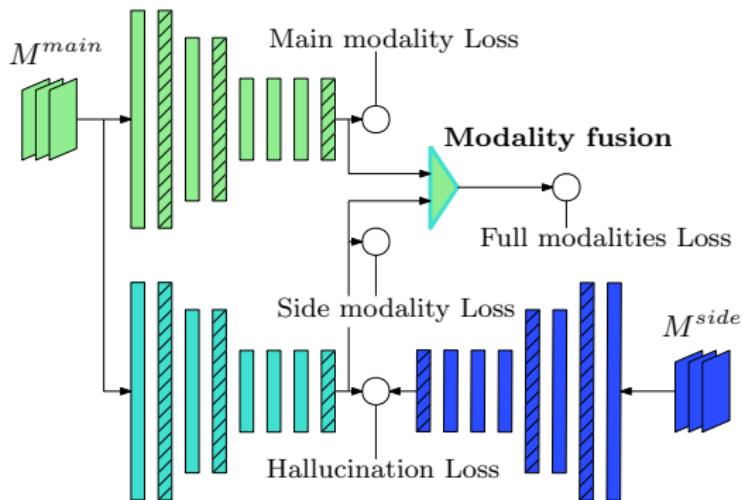


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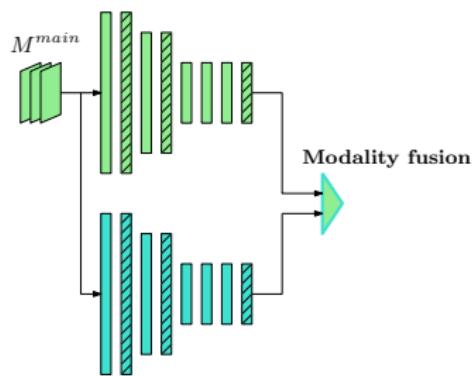
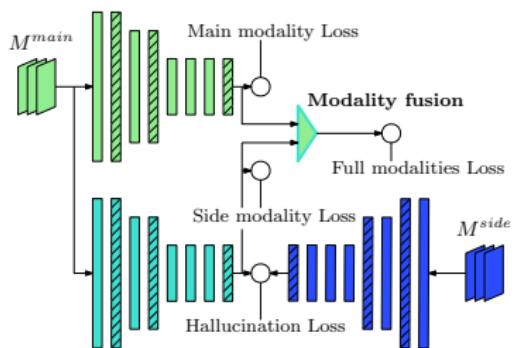
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Deployment

## **Learning side information with modality transfer**

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

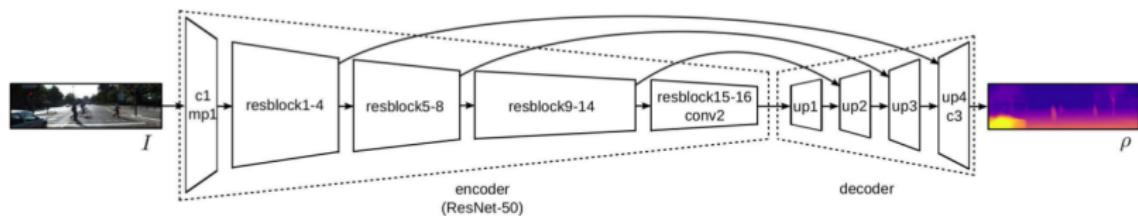
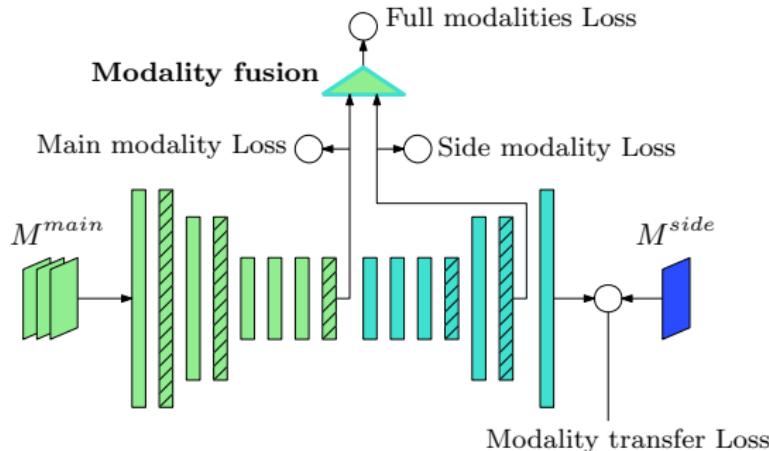


Illustration from [Kuznetsov et al., 2017]

# Proposed architecture

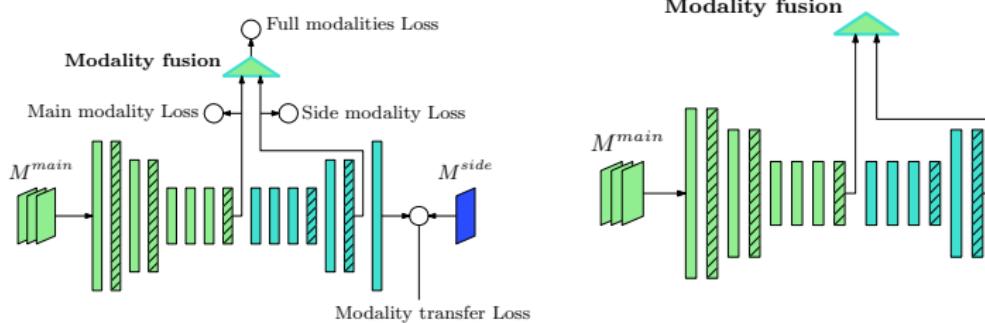
The proposed architecture inspired by encoder-decoder networks:



Training

# Proposed architecture

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Deployment

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

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



# Optimization

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Final loss:

$$\begin{aligned} \text{Loss} = & \text{Loss}_{\text{triplet}}^{\text{main}} + \text{Loss}_{\text{triplet}}^{\text{side}} * \sigma_{\text{side}} \\ & + \text{Loss}_{\text{triplet}}^{\text{full}} * \sigma_{\text{full}} + \text{Loss}_{\text{transfer}} * \sigma_{\text{transfer}}. \end{aligned} \quad (3)$$



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Diversification loss:

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

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



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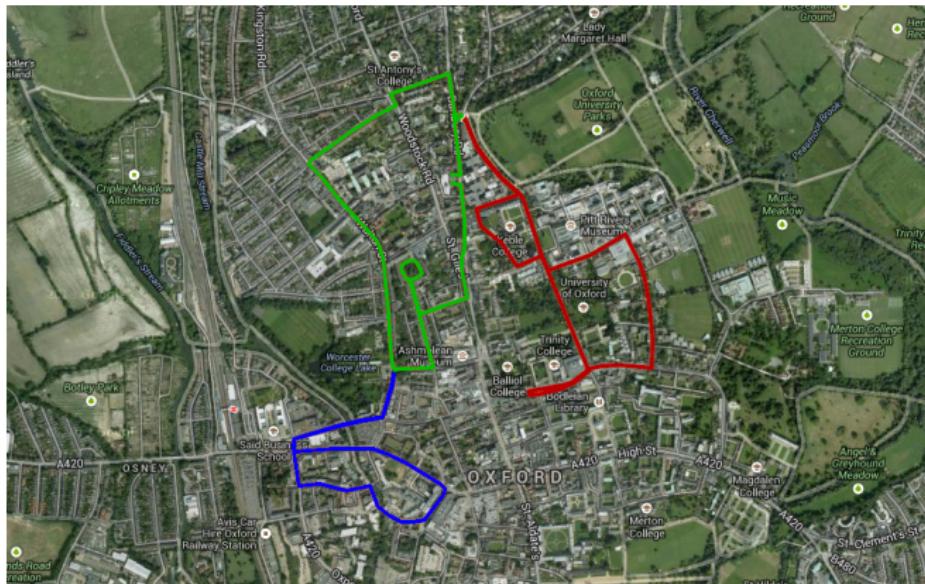
- No need of pretraining on side modality
- Method by nature lighter: 29k parameters vs. 41k parameters for networks built upon Alexnet architecture
- No need to transform modality into 3-channels data



## Experiments

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# Robotcar dataset



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



Experiments



# Robotcar dataset



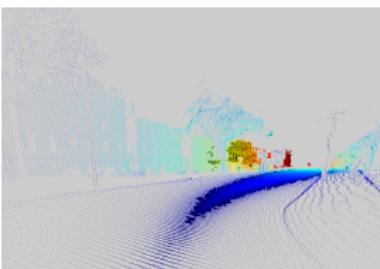
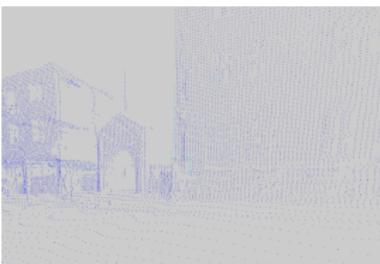
Examples of queries with corresponding dataset candidates of the testing set.

# Building dense modality map

Image



Points cloud



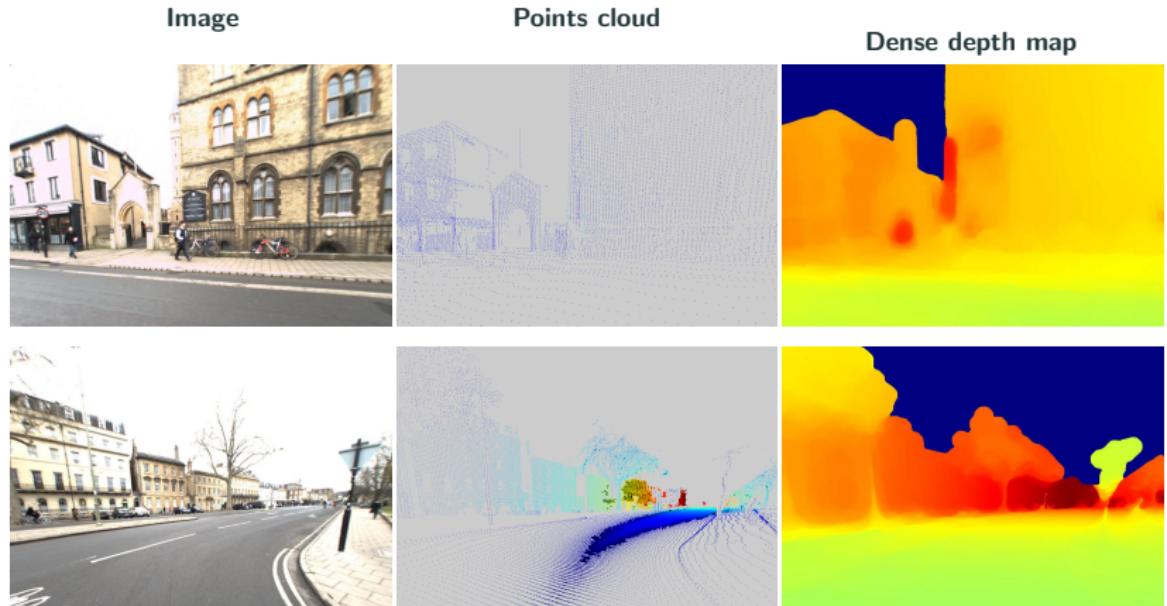
We use the algorithm proposed in [Bevilacqua et al., 2017] to create a dense modality map from an image and the associated point cloud.



Experiments

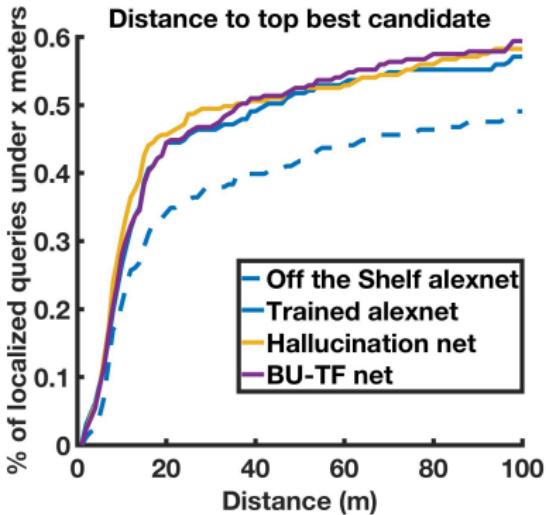
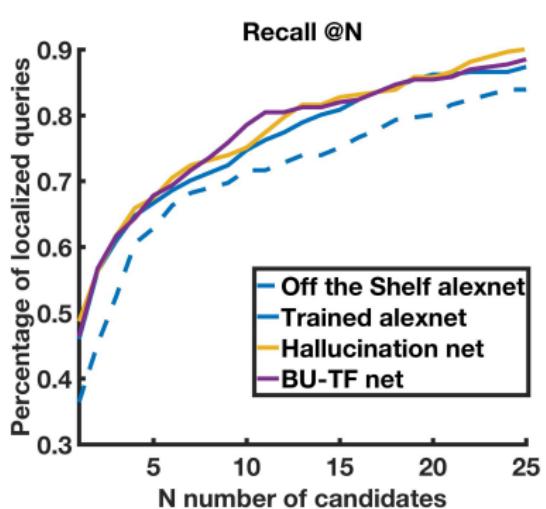


# Building dense modality map



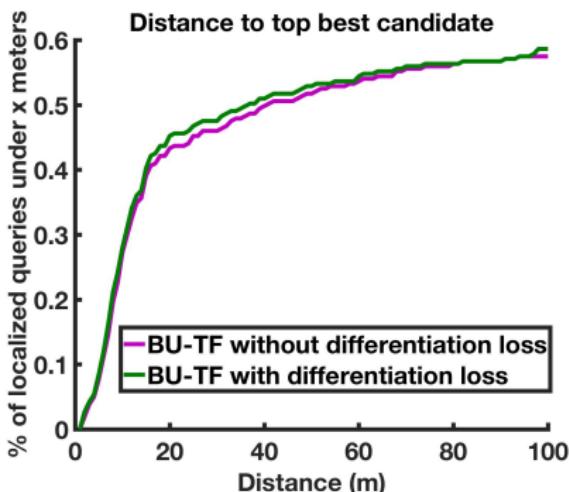
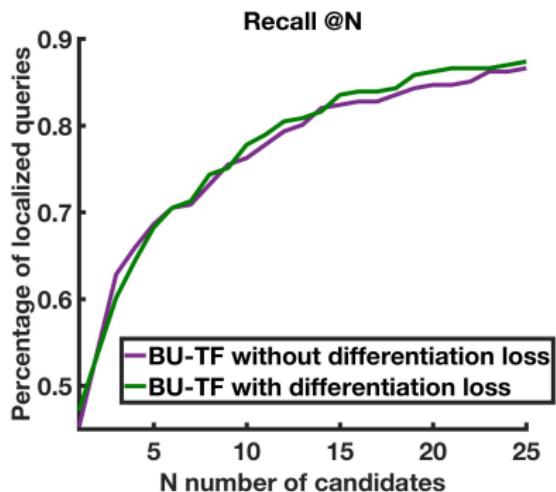
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# Results



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

## Results - Diversification loss

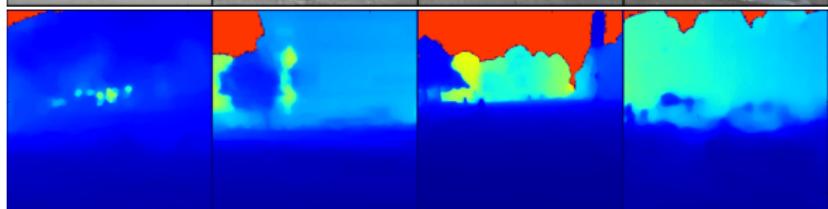


## Results - Visual inspection

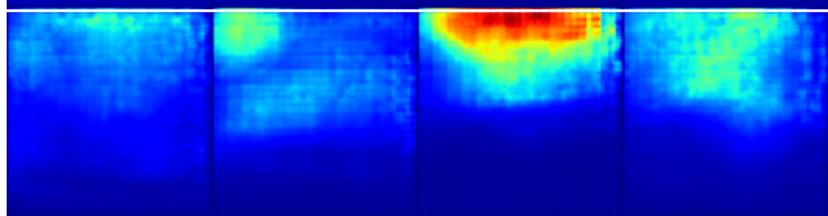
Main modality



Side modality



Reconstructed  
side modality



## Conclusion

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New method for learning with modality side modality have been presented.  
BU-TF is more efficient than hallucination as it needs less training time have less parameters while producing comparable results.



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- 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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