Spherical Convolutional Neural Networks

Empirical analysis of SCNNs

LTS2

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Master Thesis - Frédérick Gusset

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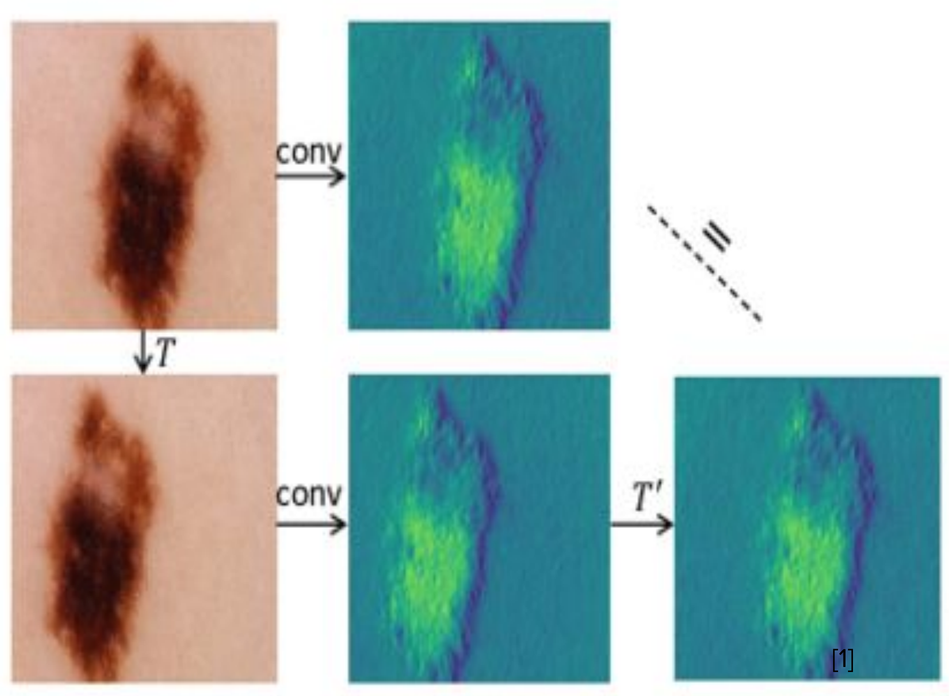
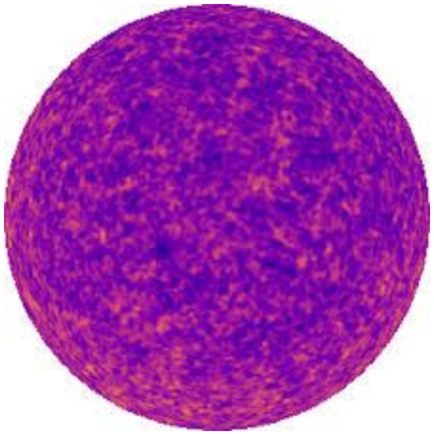
Introduction

- CNNs are very powerful tools in Deep Learning
  - Equivariance to translation



Introduction

- Different symmetries such as rotations
  - Use of sphere S^2 or SO(3) domain

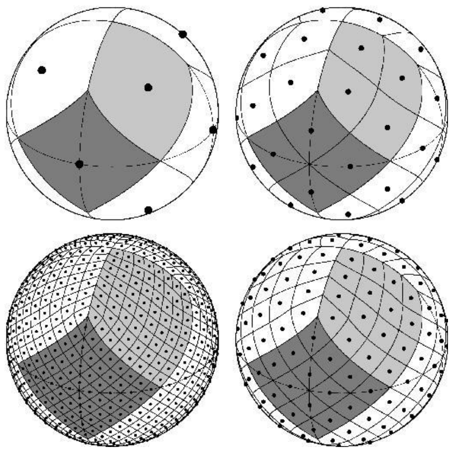


Cosmological maps [2]

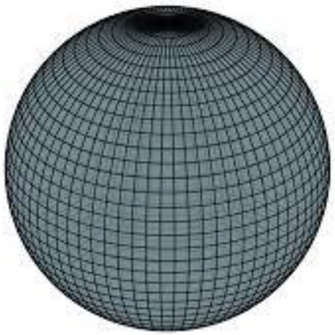
3D objects

Omnidirectional imaging [3]

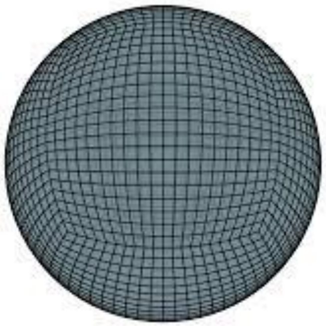
Sphere representation



HEALPix [4]



Equiangular [2]



Polyhedron [2]

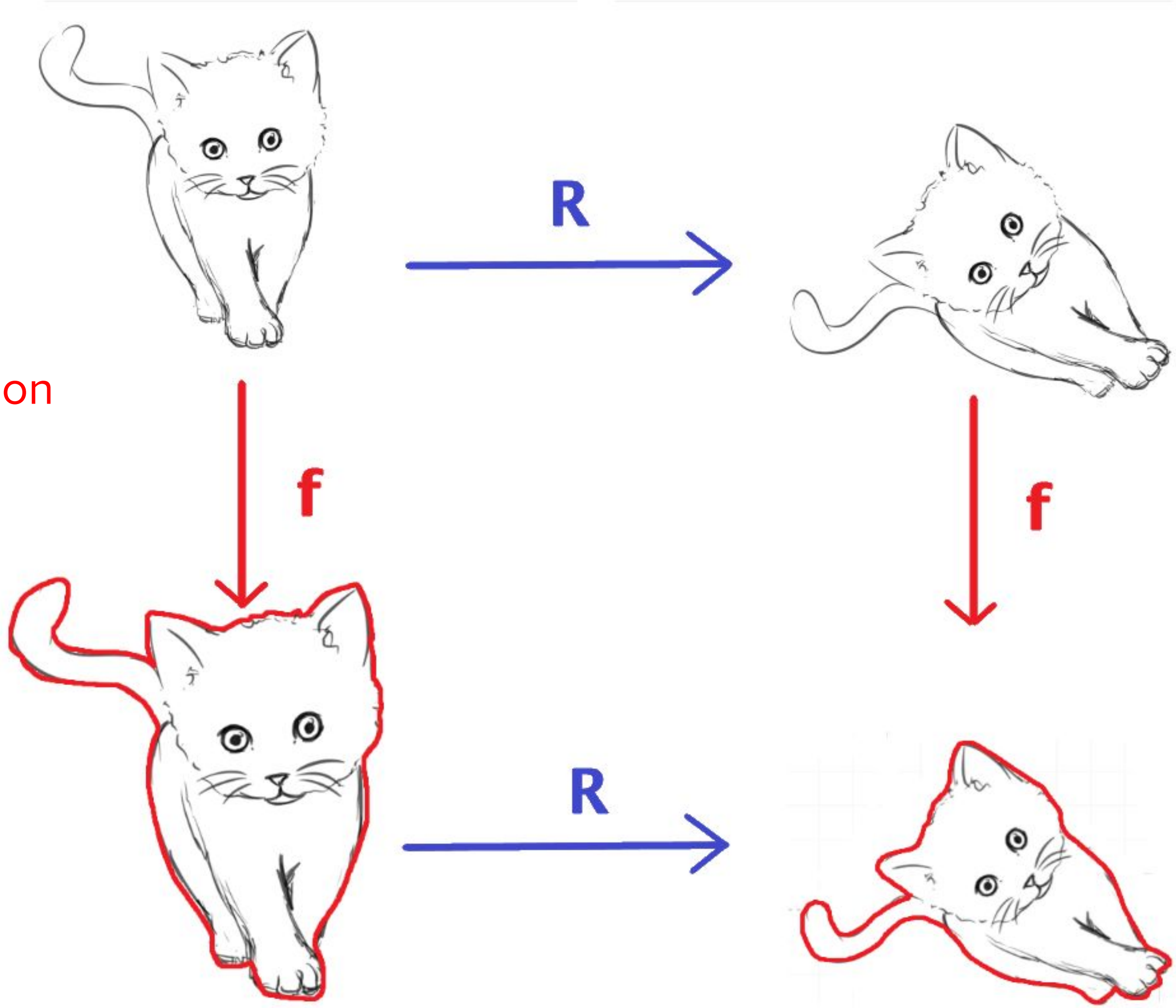
- Iso-latitude
- Same area coverage
- Hierarchical

Equivariance

Example:

Segmentation

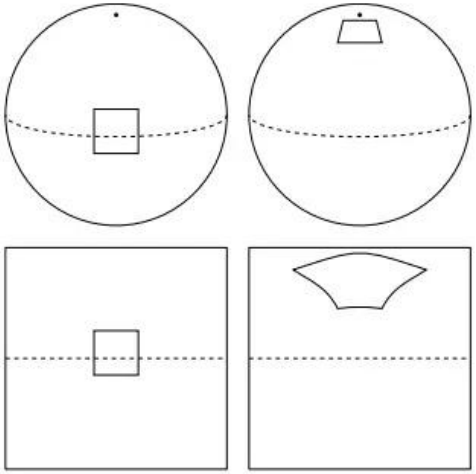
Rotation



[5]

Spherical CNNs

- 2D CNNs on planar projection
  - not desired rotation equivariance



Planar projection [6]

Spherical CNNs

- 2D CNNs on planar projection
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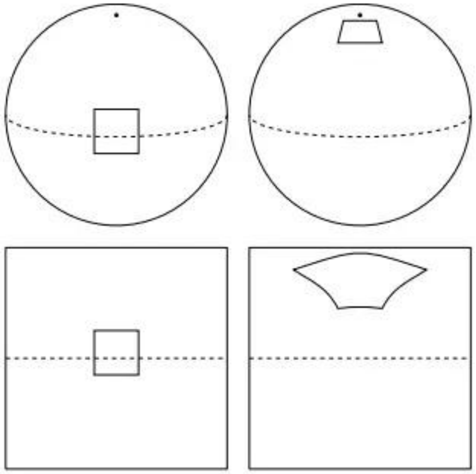
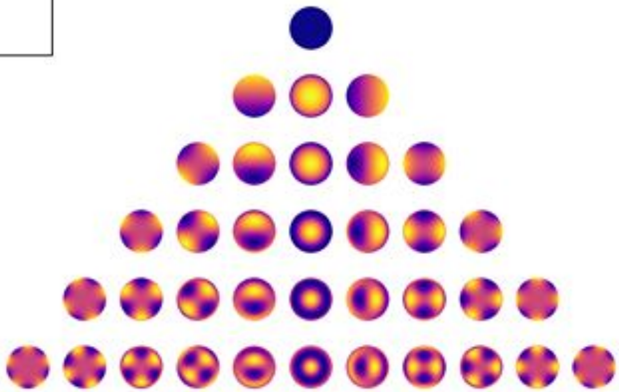


Planar projection [6]

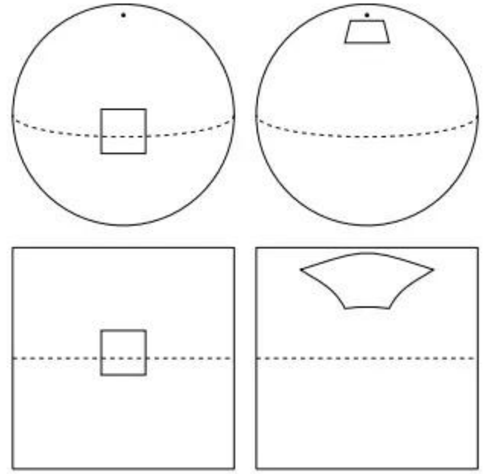
- Spherical Fourier Transform
  - computationally expensive



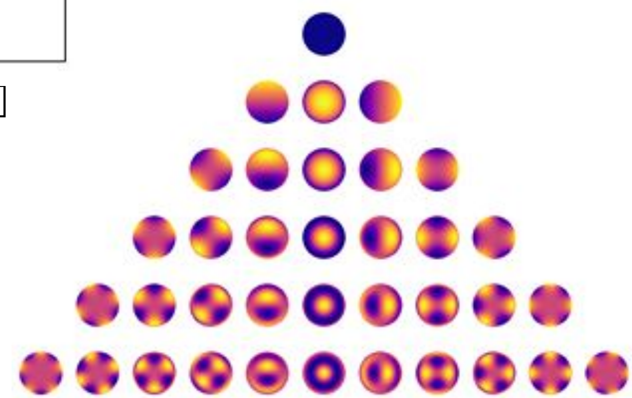
Spherical Harmonics [7]

Spherical CNNs

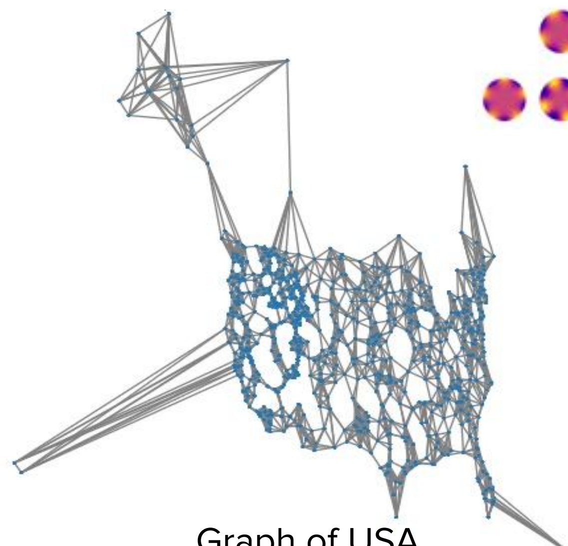
- 2D CNNs on planar projection
    - not desired rotation equivariance
- Spherical Fourier Transform
    - computationally expensive
- Graph CNN



Planar projection [6]

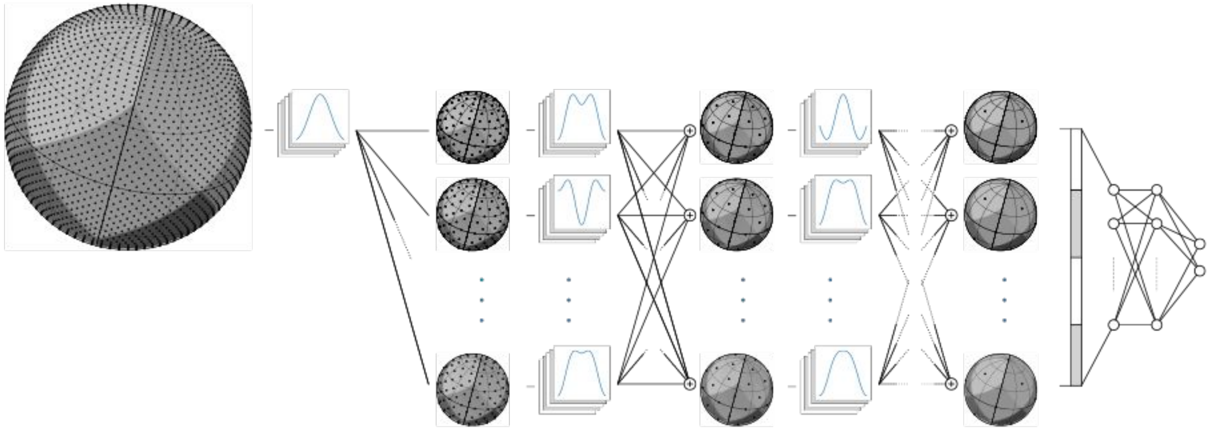


Spherical Harmonics [7]



Graph of USA

DeepSphere

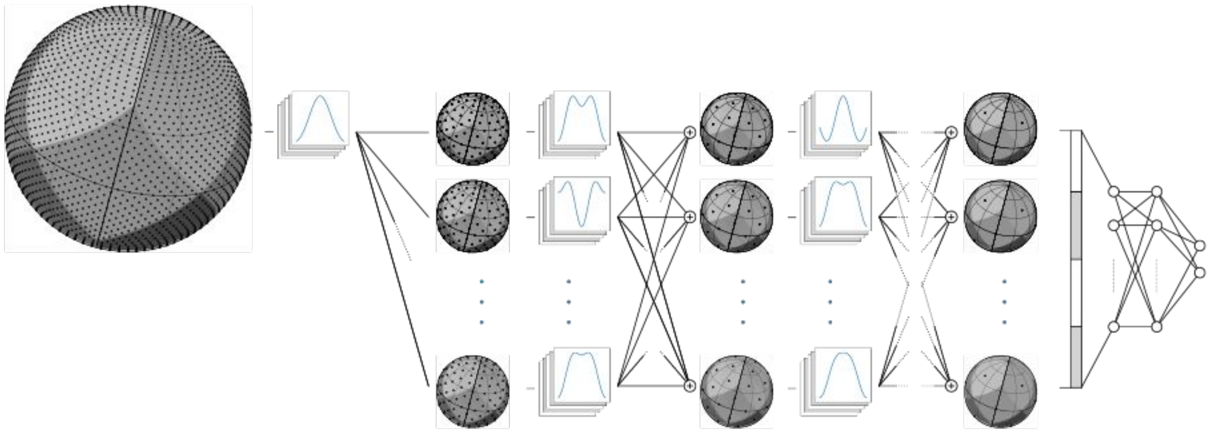


[2]

Advantages

- Similar to standard CNN (computationally efficient)
- Can operate with any graph (flexible)

DeepSphere



[2]

Advantages

- Similar to standard CNN (computationally efficient)
- Can operate with any graph (flexible)

Differences

- Almost rotation equivariant (graph construction)
- Equivariant only on S^2, but invariant to 3rd rotation of $SO(3)$

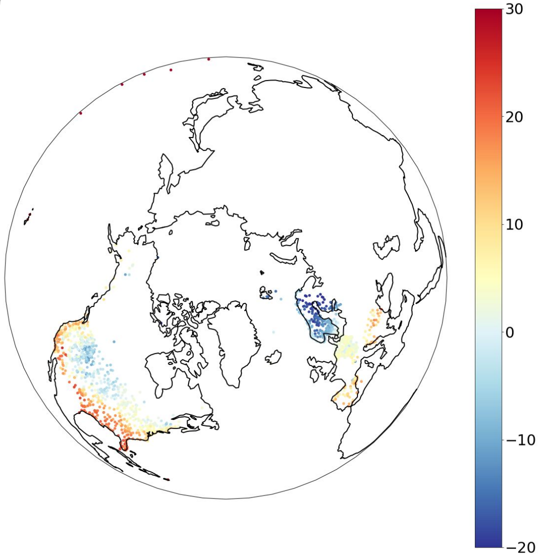
Different tasks

- Shape retrieval and classification
  - SHREC17 and ModelNet40

Different tasks

- Shape retrieval and classification
  - SHREC17 and ModelNet40

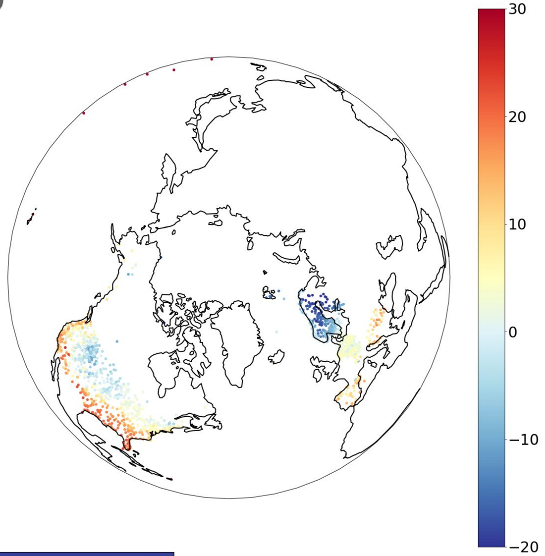
- Global and Dense regression
  - GHCN-daily, planetarian data



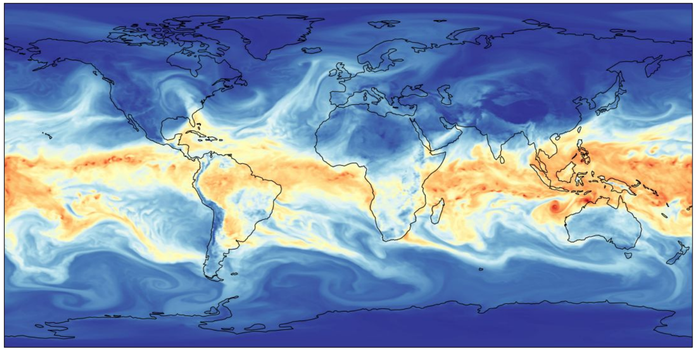
Different tasks

- Shape retrieval and classification
  - SHREC17 and ModelNet40

- Global and Dense regression
  - GHCN-daily, planetarian data



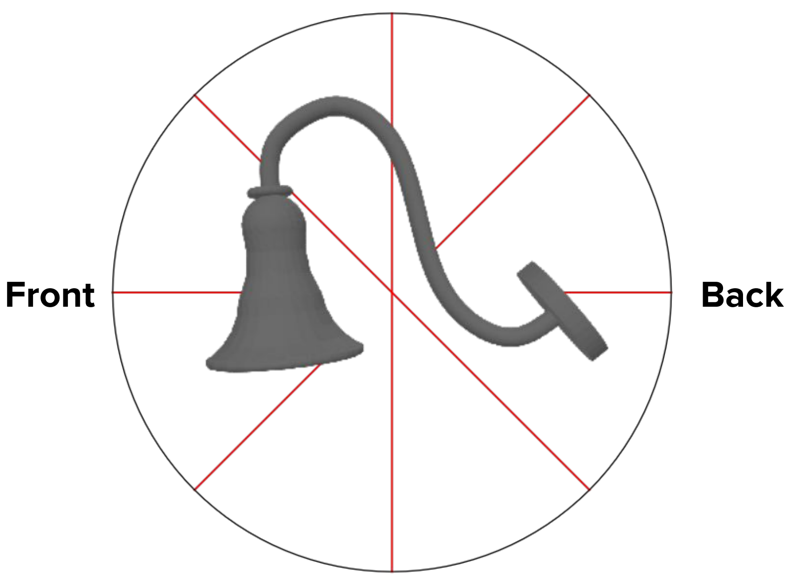
- Segmentation
  - Climate Pattern Detection



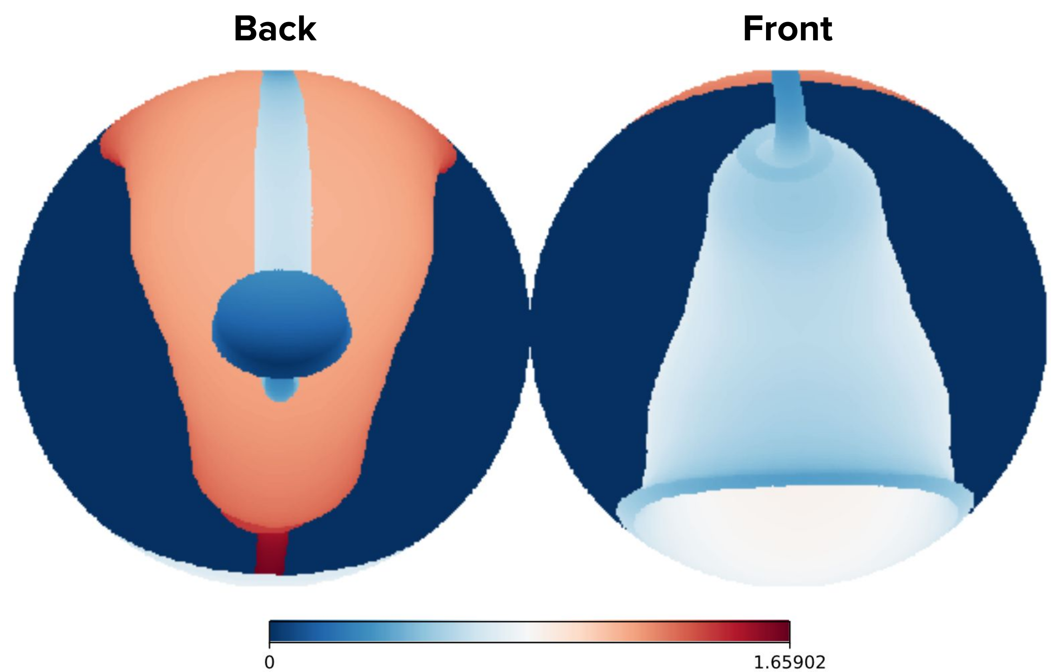
SHREC17

- Shape retrieval contest
- Spherical signal ➔ All orientations in 3D

55 classes: [airplane, drawer, lamp, ...]



Ray-casting on a sphere



Distance feature

SHREC17 - Results

	performance		size		speed *	
Method	Accuracy	mAP	params	features	inference	training
Cohen *s2cnn_simple*	78.59	66.5	400k	$2 \cdot 64$	12ms	32h
Esteves *sphericalcnn*	79.18	68.5	500k	8	9.8ms	2h52
Deepsphere *Optimal*	80.42	68.6	190k	4	1.0ms	48m

local filter

4 to 40 times faster

	performance	
Method	Accuracy	mAP
Deepsphere *Equiangular*	79.25	66.5
Deepsphere *HEALPix*	80.42	68.6

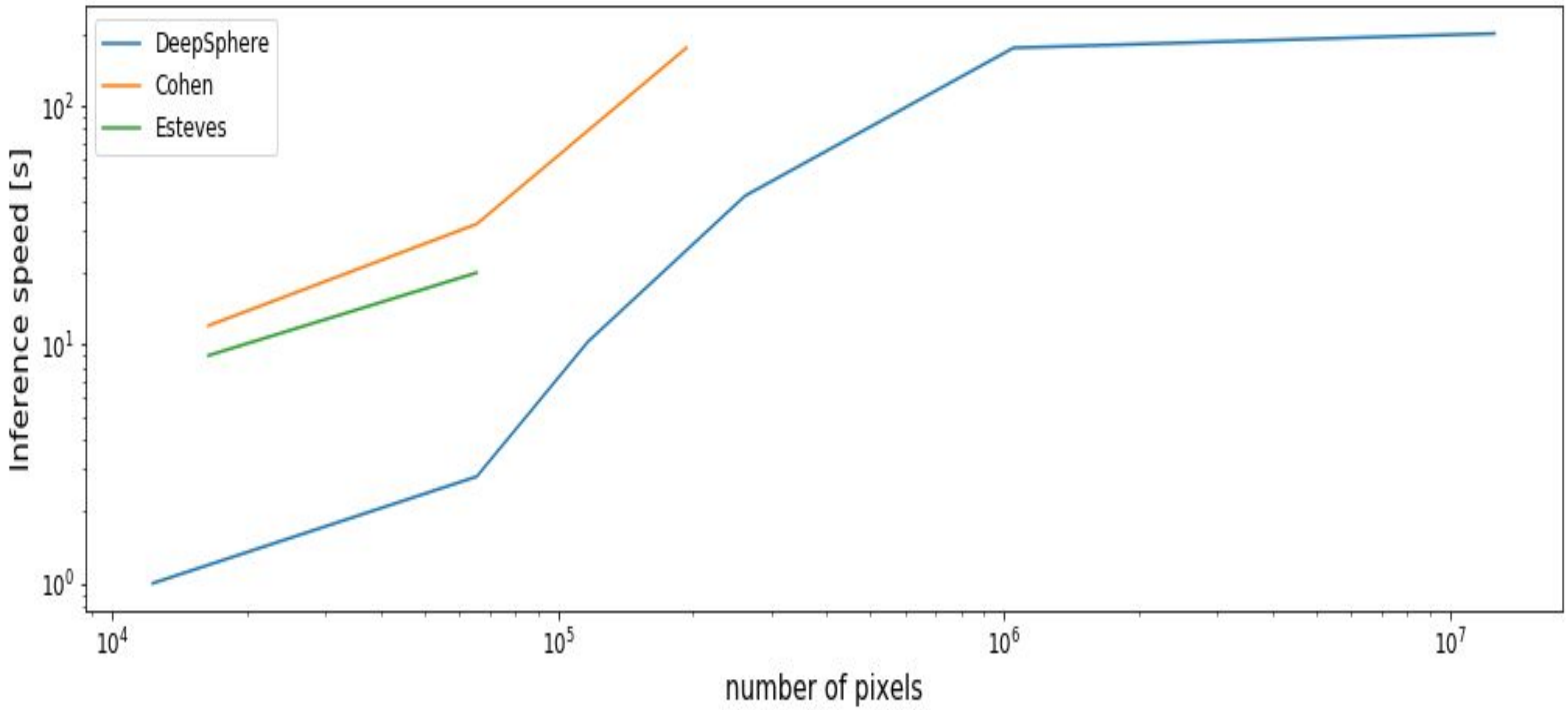
* Trained on NVIDIA GTX 1080 Ti

Equiangular

Tested on SHREC17

	performance	
Method	Accuracy	mAP
Deepsphere *Equiangular*	79.25	66.5
Deepsphere *HEALPix*	80.42	68.6

SHREC17 - Time evaluation

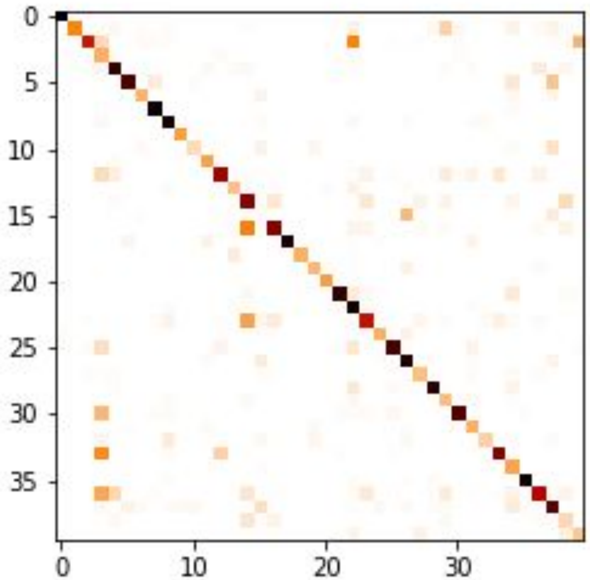


ModelNet40

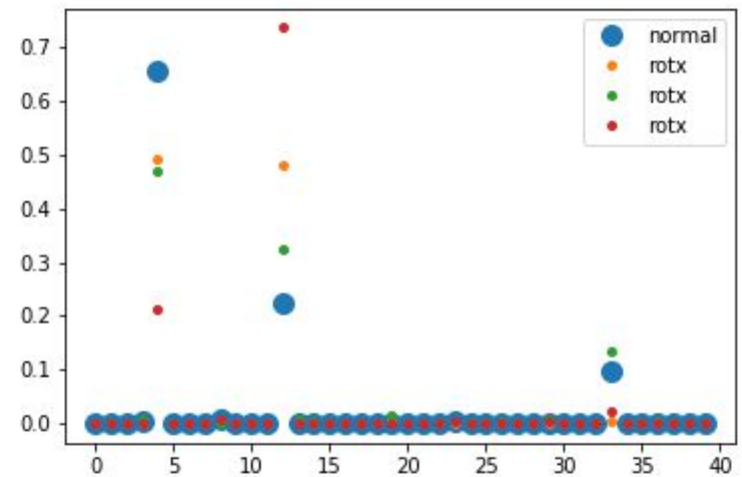
- Shape classification - similar to SHREC17

Accuracy	x/x	z/z	SO3/SO3	z/SO3
Cohen	85.0	-	-	-
Jiang	90.5	-	-	-
Esteves *scnn*	-	88.9	86.9	78.6
DeepSphere	87.8	86.8	86.7	76.9

ModelNet40



Confusion matrix

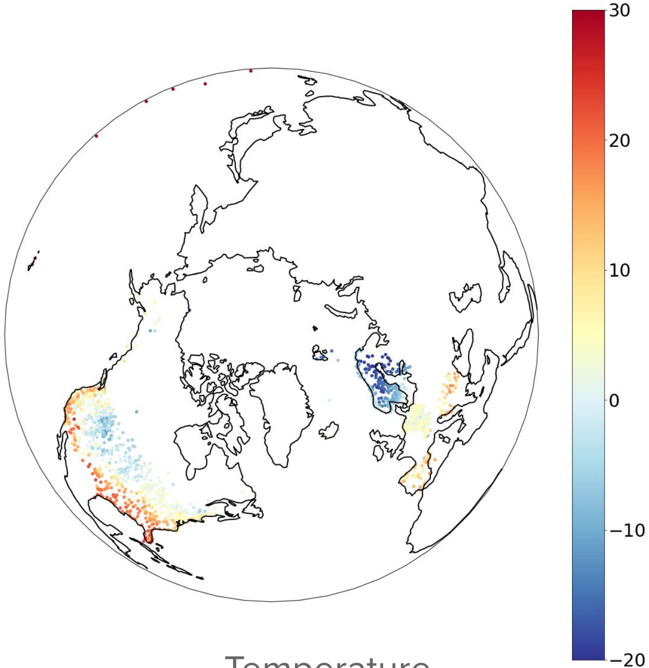


Logits evolution

GHCN-daily

- Non-uniform sampling ➔ prove DeepSphere flexibility

- No specific task



Temperature
over the globe

GHCN-daily

Dense regression

Find future temperature

order	MSE	MAE	MRE	R2
0	10.88	2.42	83.8	0.896
1	8.91	2.20	75.1	0.906
4	8.20	2.11	73.2	0.919
9	8.38	2.12	73.3	0.915

GHCN-daily

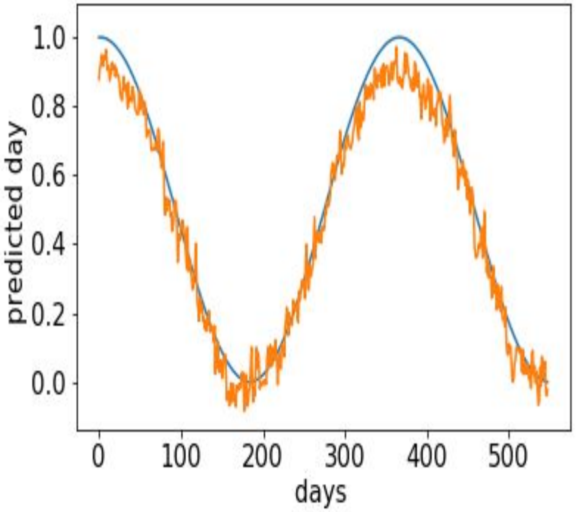
Dense regression

Find future temperature

order	MSE	MAE	MRE	R2
0	10.88	2.42	83.8	0.896
1	8.91	2.20	75.1	0.906
4	8.20	2.11	73.2	0.919
9	8.38	2.12	73.3	0.915

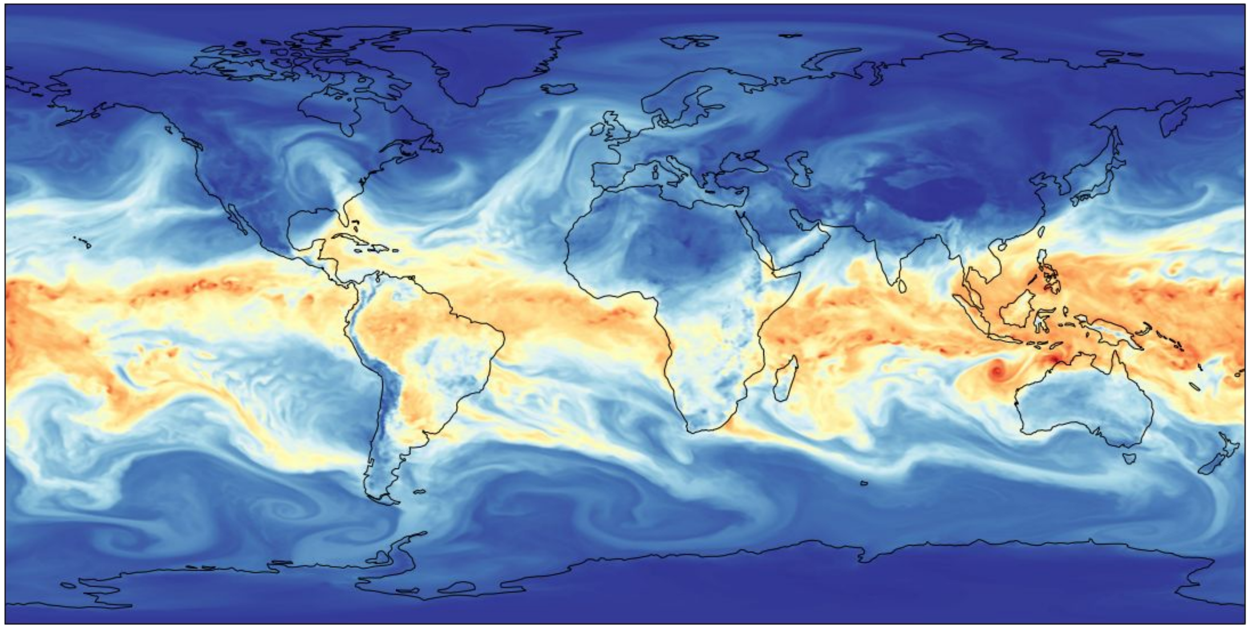
Global regression

Find day in year



Climate Pattern Detection

- Segmentation problem



Climate Pattern Detection

Results

	Accuracy				
Method	BG	TC	AR	mean	mAP
Mudigonda et al.	97	74	65	78.67	-
Jiang et al.	97	94	93	94.67	-
Cohen et al. (R2R)	97.4	97.9	97.8	97.7	75.9
Deepsphere	97.9	96.0	97.9	97.9	83.6

Conclusion

- Computationally 4 to 40 times faster
- Similar results to the other SCNNs
  - Invariance to 3rd rotation is an unnecessary price to pay
- Sufficiently equivariant to rotation
- Works on any sampling, as long as a graph is built and pooling operation adapted

Thanks for your attention

Questions?

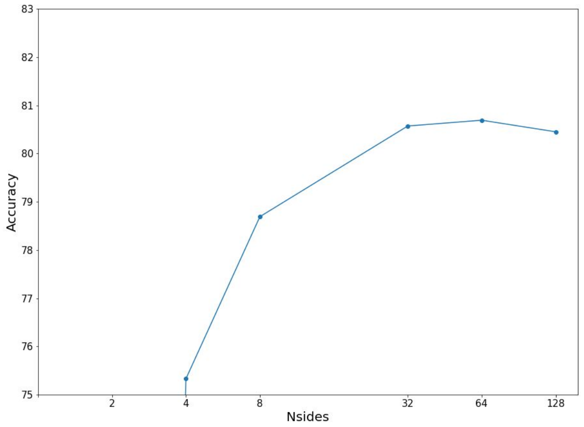
Equivariance to rotation

$N_{side} = 32$

	NR/NR	R/NR	R/R	NR/R
Accuracy	79.57	79.26	79.25	79.82
mAP@N	67.1	67.0	67.5	67.4

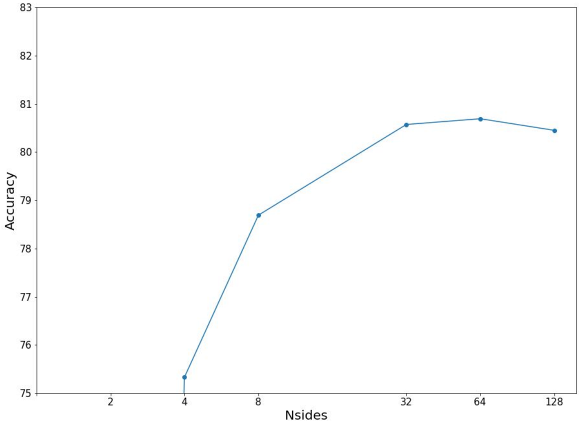
New graph

- Sampling density



New graph

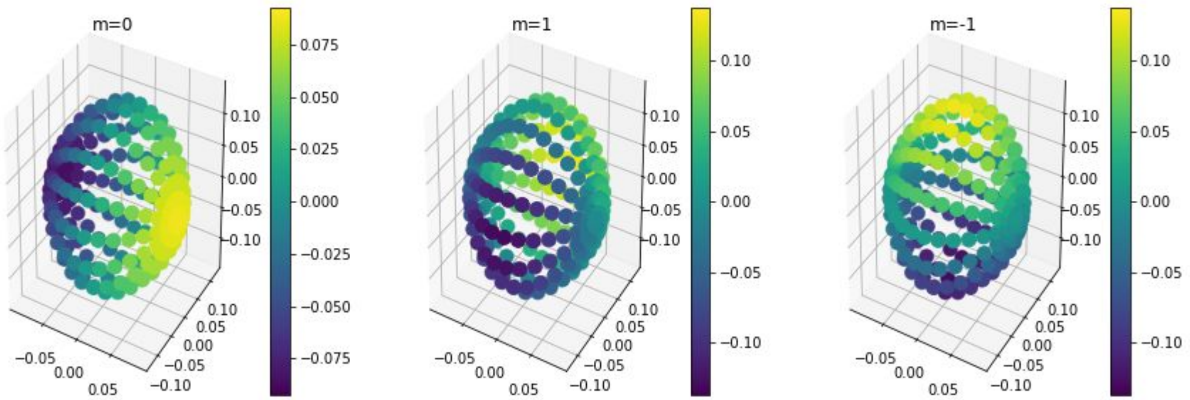
- Sampling density



- DeepSphere V2

	old graph	new kernel size	new graph
accuracy	82.23	82.45	82.76

Equiangular



Overfit

	∅	Regularization	Dropout	DropFilter	Triplet Loss	Data aug.
Accuracy	81.8	80.7	82.4	81.5	82.5	83.4

Bibliography

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6. Cohen et al., 2018
7. Starry documentation (rodluger.github.io/starry)