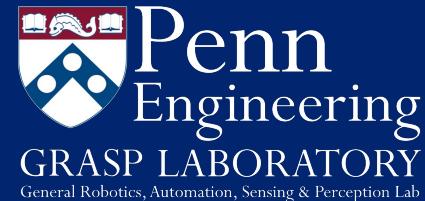




# Google Research



# Cross-Domain 3D Equivariant Image Embeddings

Carlos Esteves



Avneesh Sud



Zhengyi Luo



Kostas Daniilidis



Ameesh Makadia



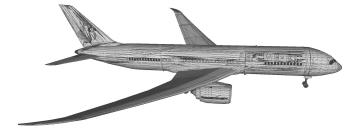
# Universal image embeddings



encode

?

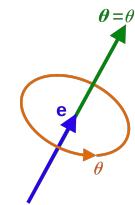
reconstruction



view synthesis



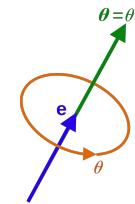
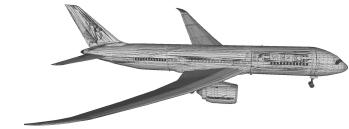
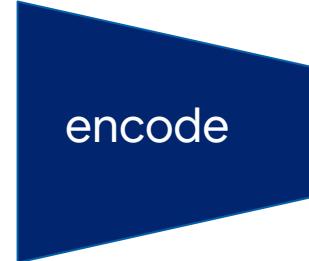
pose estimation



segmentation



# Why is this hard?



# Why is this hard?



encode



?

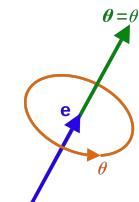
reconstruction



view synthesis



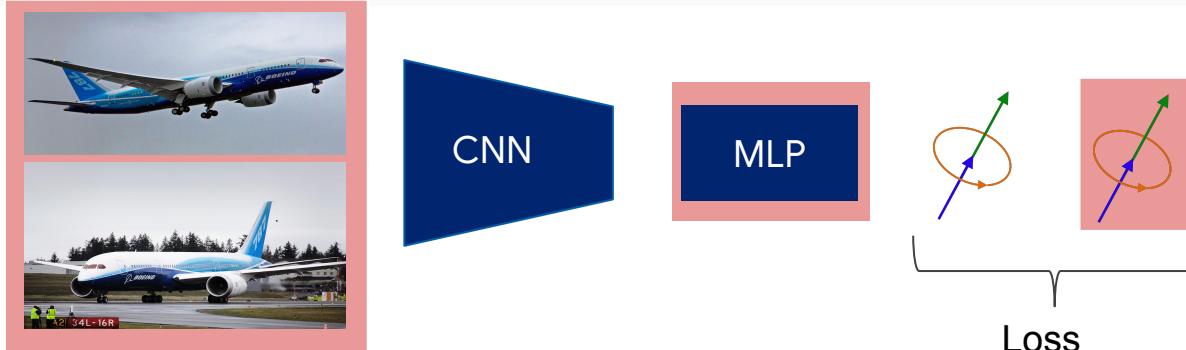
pose estimation



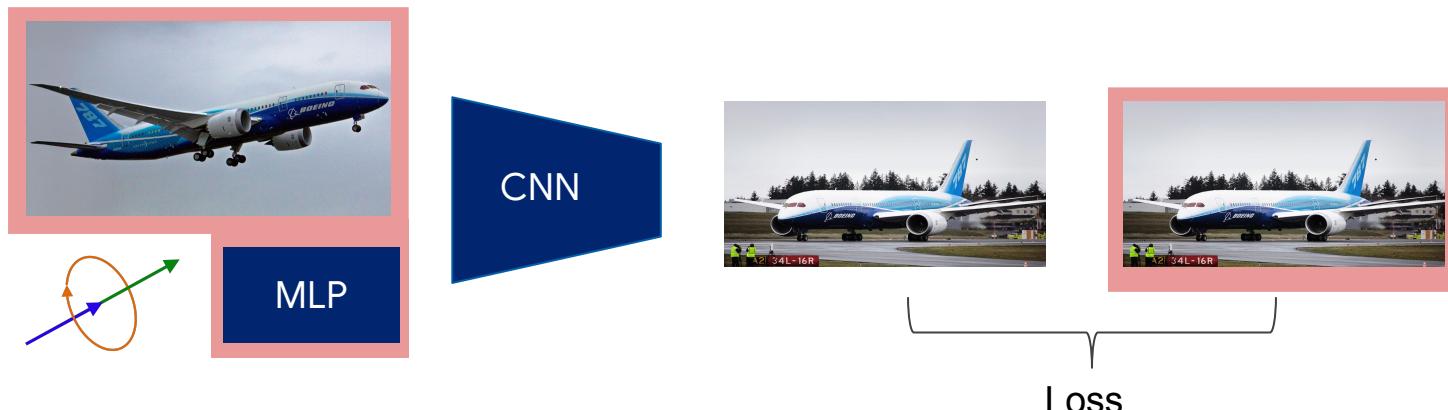
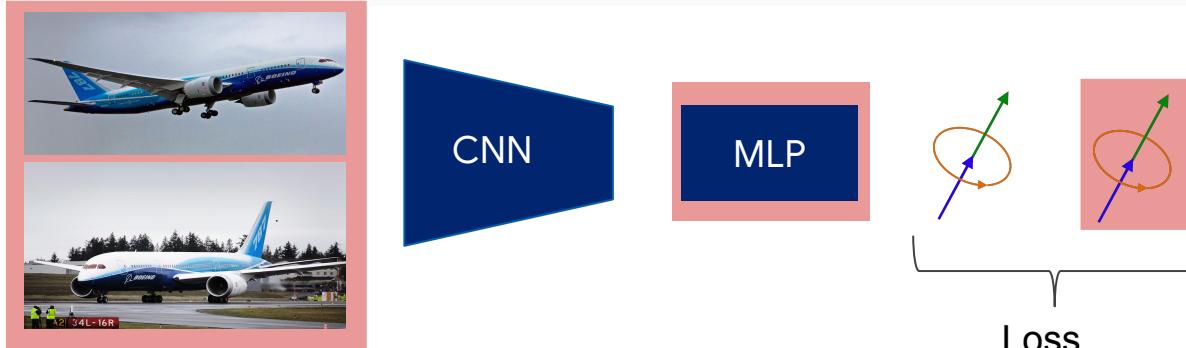
segmentation



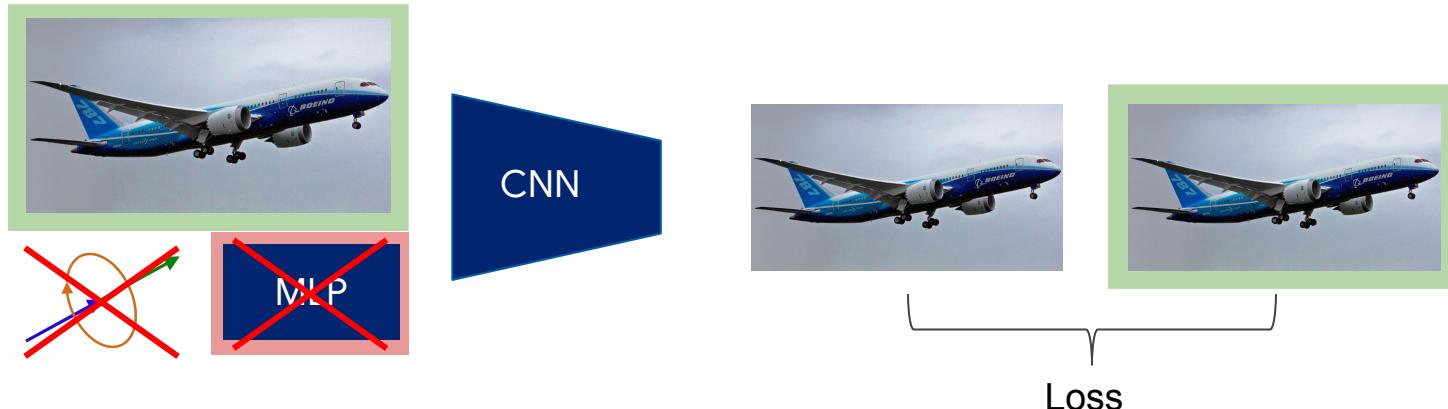
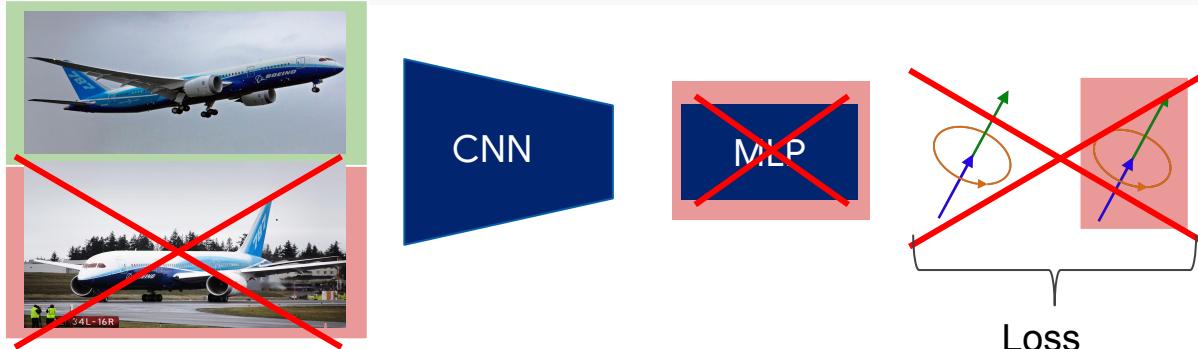
# Conventional approaches



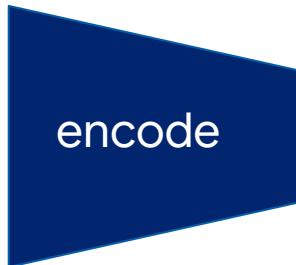
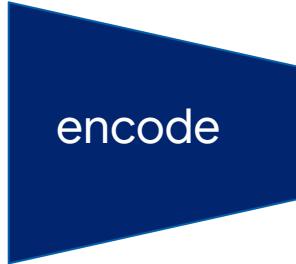
# Conventional approaches



# Our approach



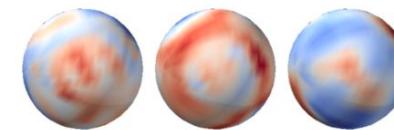
# 3D equivariant embeddings



# Embeddings on the sphere!



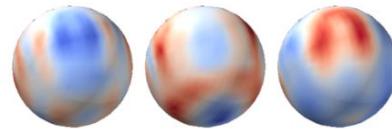
encode



...

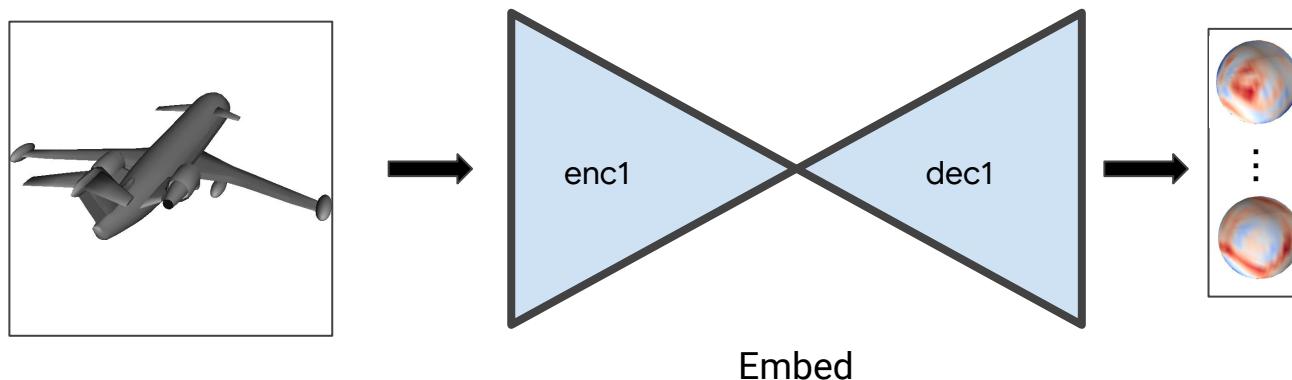


encode

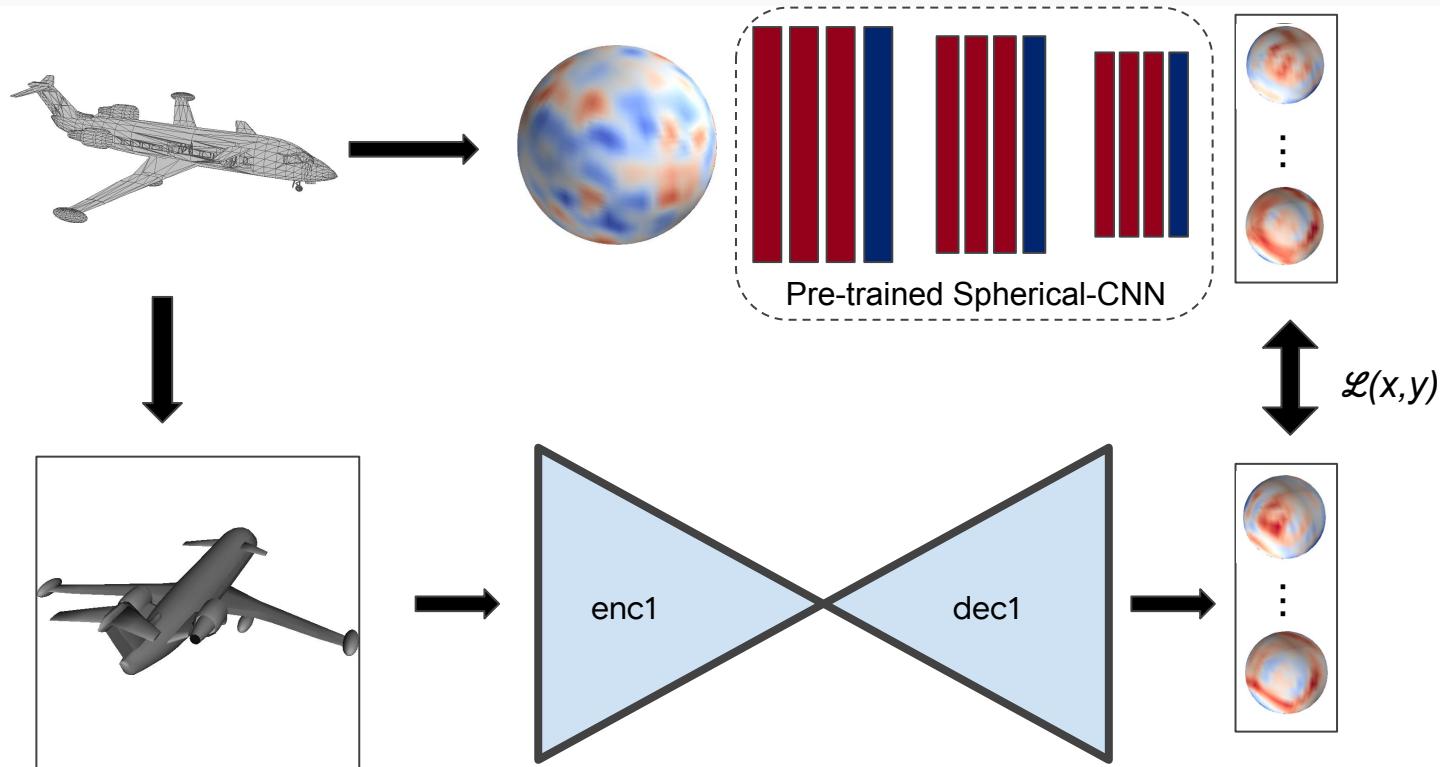


...

# How to learn cross-domain embeddings?

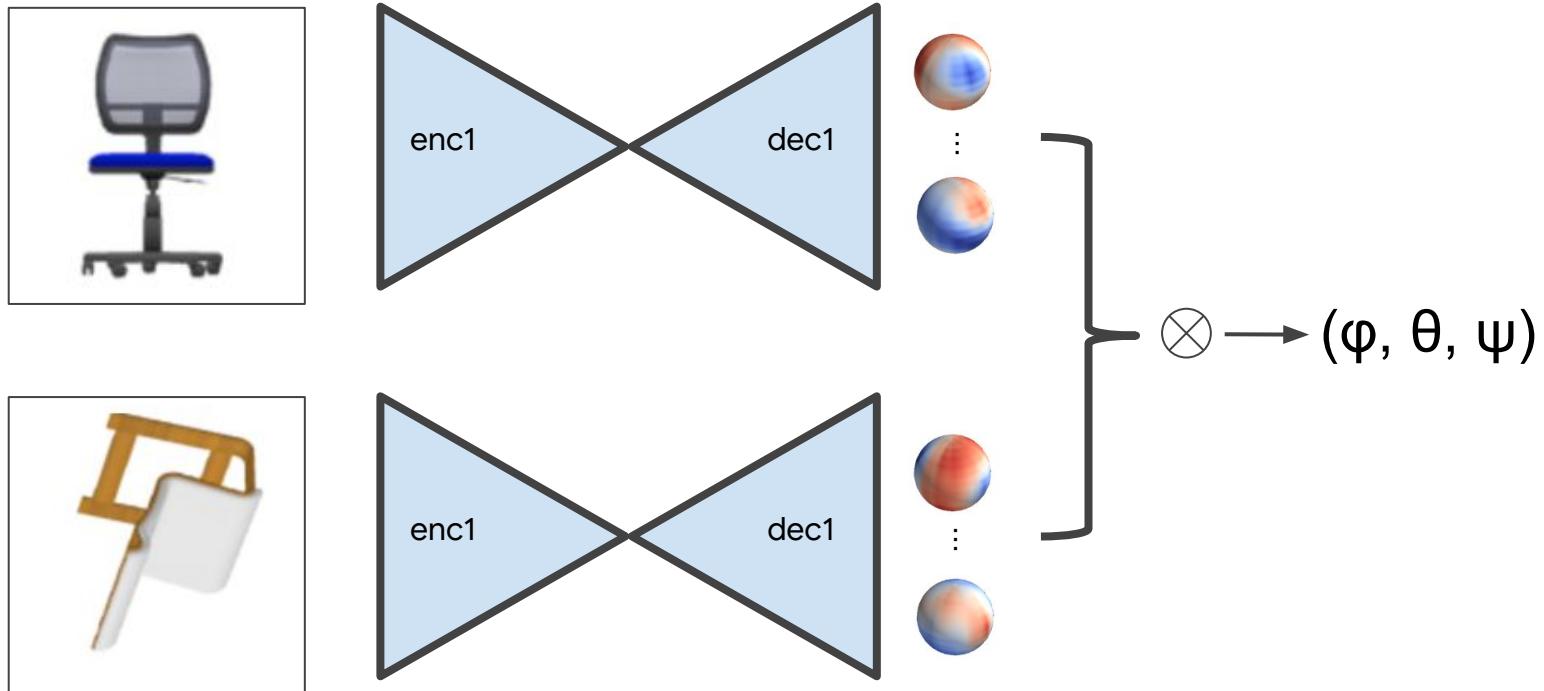


# What is the supervision?



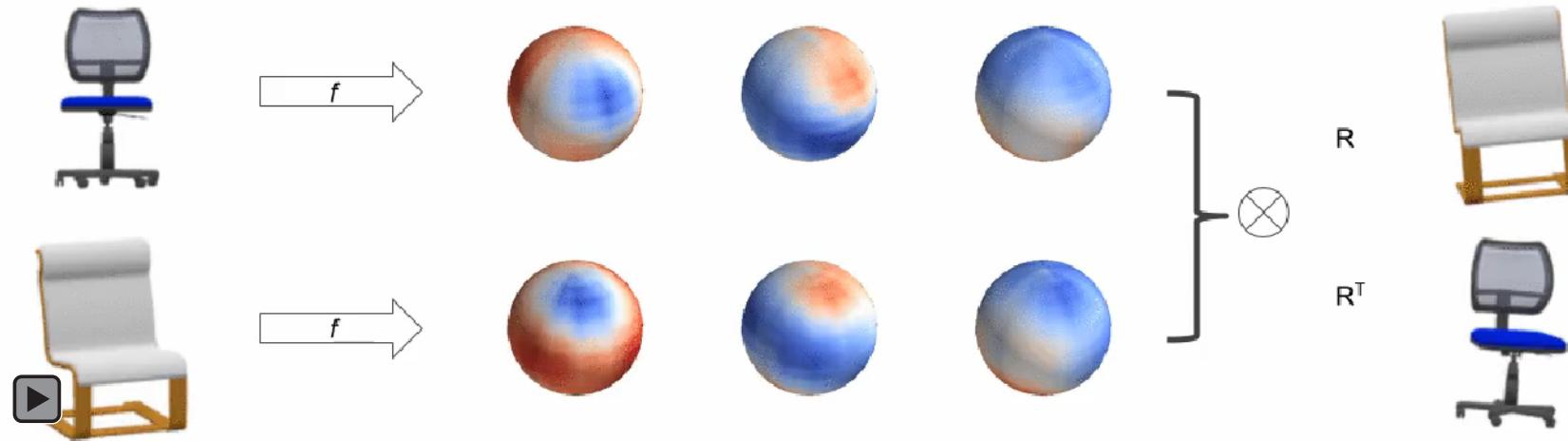
No task-specific supervision!

# Relative pose estimation



No pose regression/supervision!

# Relative pose estimation



Inputs

Embeddings

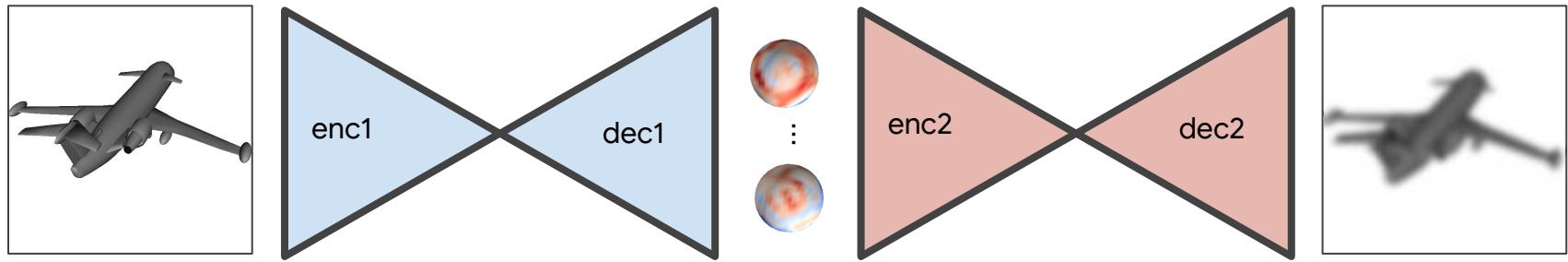
A to pose of B  
B to pose of A

# Results on real images from ObjectNet3D



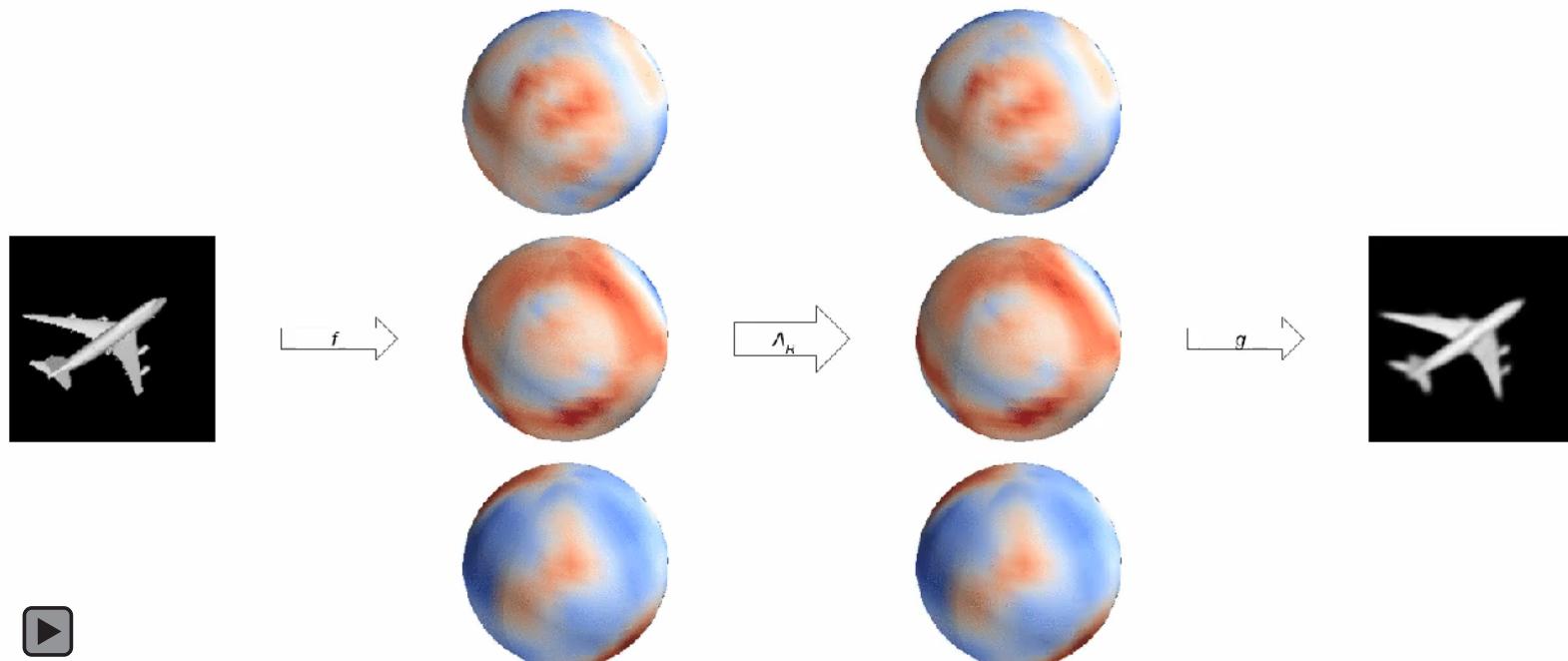
Ours: **13.75 deg**, Regression: 36.52 deg (median error).

# Novel view synthesis



Training time: reconstruct the input

# Novel view synthesis



Test time: generate any view from any other view

# Conclusion

A novel approach to learning geometric image embeddings

- equivariant to 3D rotations
- needs only unaligned meshes as training inputs
- generalizes to geometric tasks without typical task-specific supervision
  - e.g. no pose or view synthesis supervision
- avoids the difficulties of traditional approaches
  - e.g. no pose regression or full 3D structure prediction

# Cross Domain 3D Equivariant Image Embeddings

06:30 -- 09:00 PM @ Pacific Ballroom #25

