Details on Project Updates (Next Tuesday, Nov 28th)

- On Nov 28th, each group will give a **2 minute update** to their project
  - Heilmeier Questions
  - Results of simple experiment
  - Definition & anticipated results of final experiment
- Goal: Give you a low-risk platform to train your public & scientific speaking skills

RECAP

Geometric Deep Learning

Geometric guarantees (equivariance)

CNNs are translation equivariant

Via convolutions

Slide curtesy of Erik Bekkers from UVA Deep Learning II Course

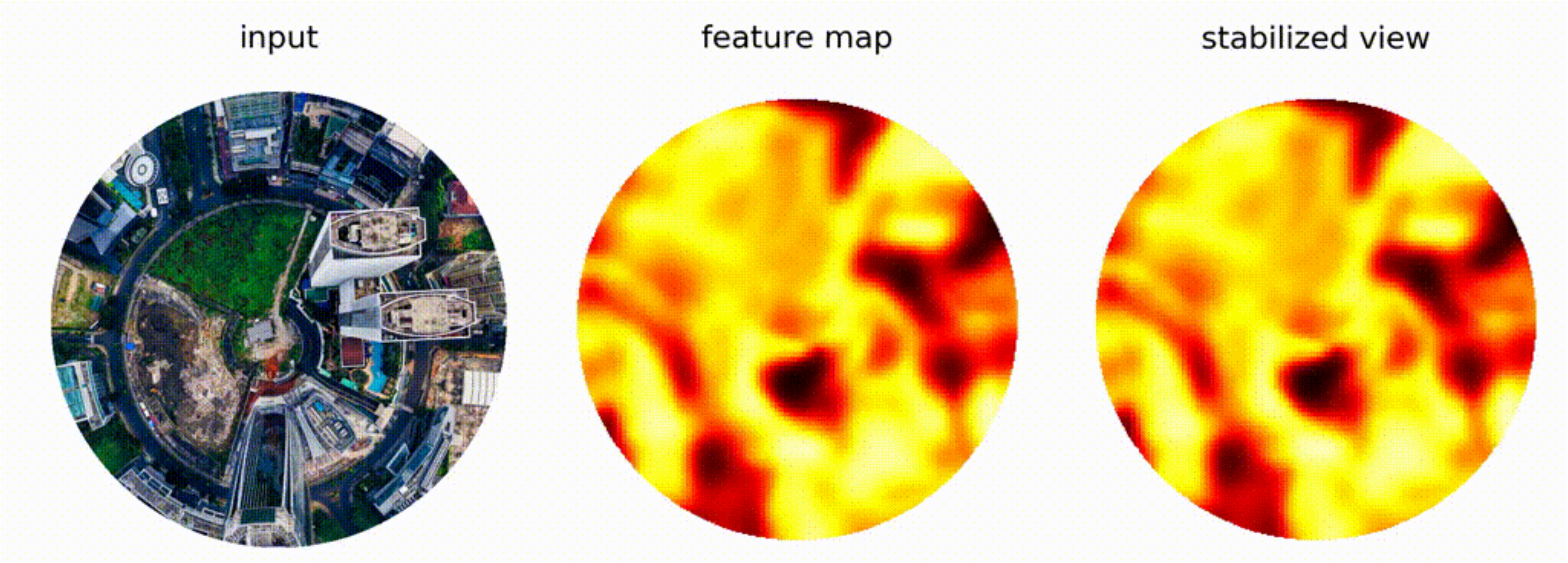
Geometric guarantees (equivariance)

CNNs are translation equivariant

Via convolutions

Geometric guarantees (equivariance)

Normal CNN

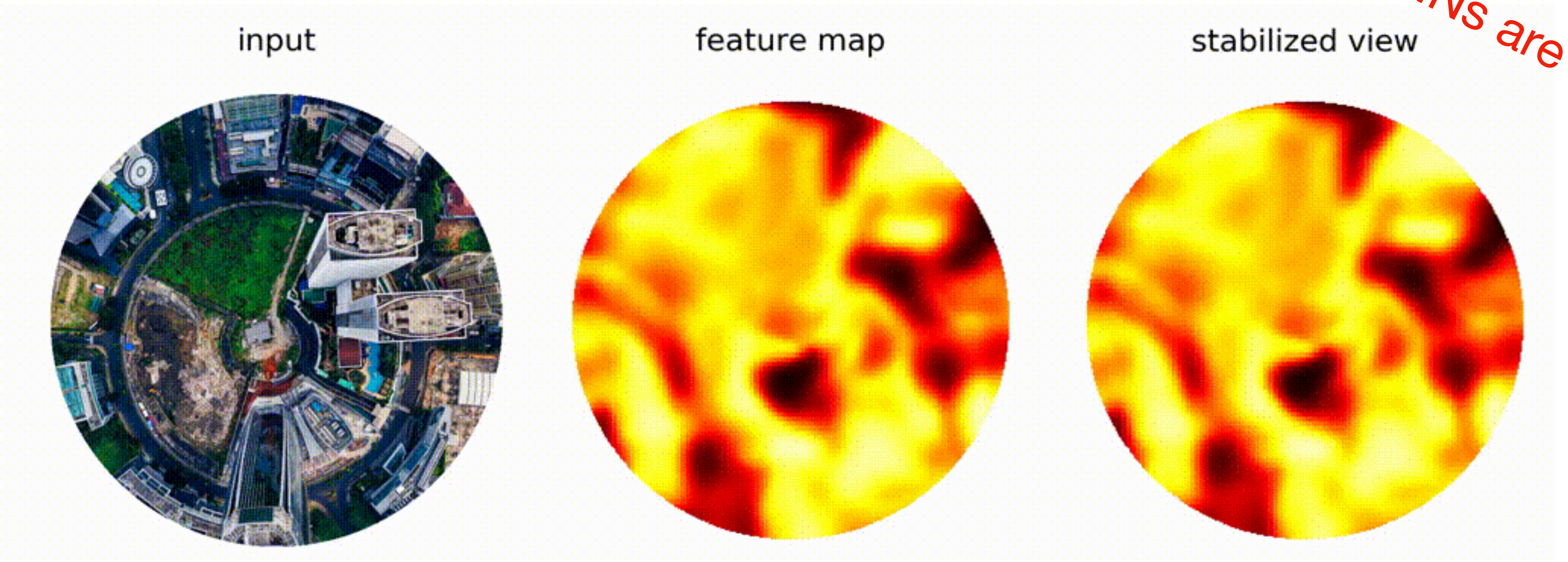


Figures source:
https://github.com/QUVA-Lab/e2cnn

Slide curtesy of Erik Bekkers from UVA Deep Learning II Course

Geometric guarantees (equivariance)

Normal CNN



CNNs are not rotation equivariant

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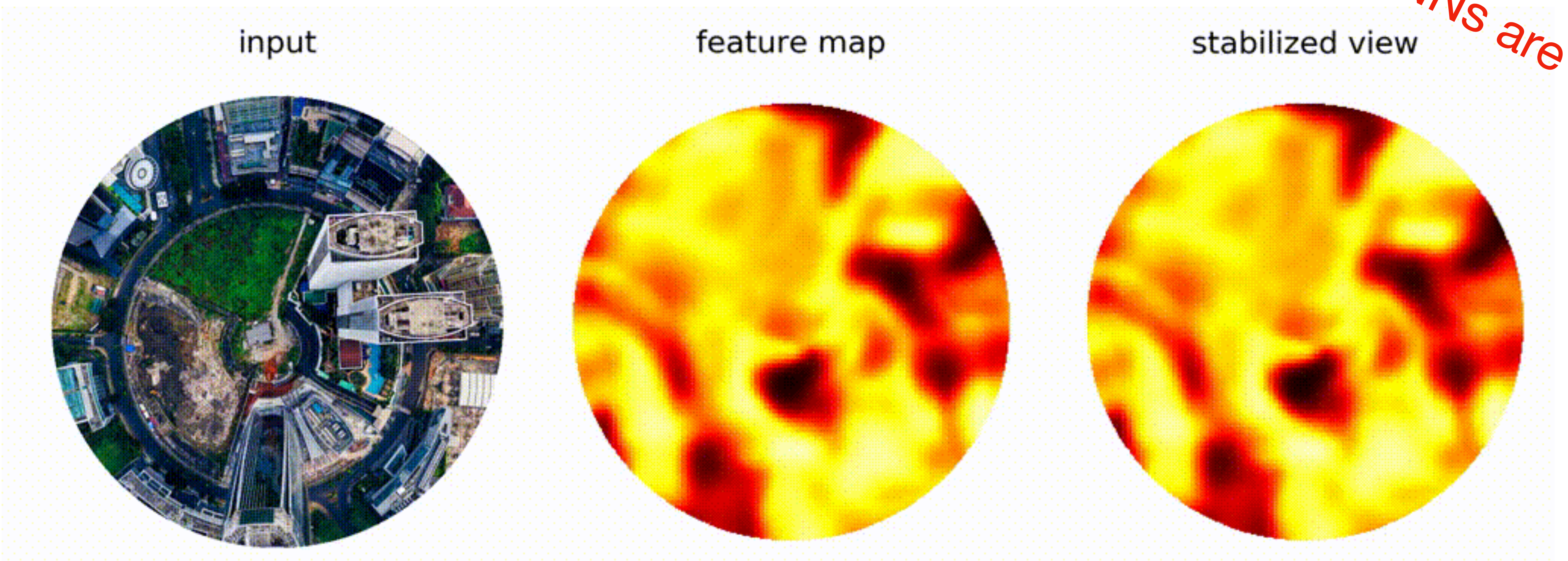
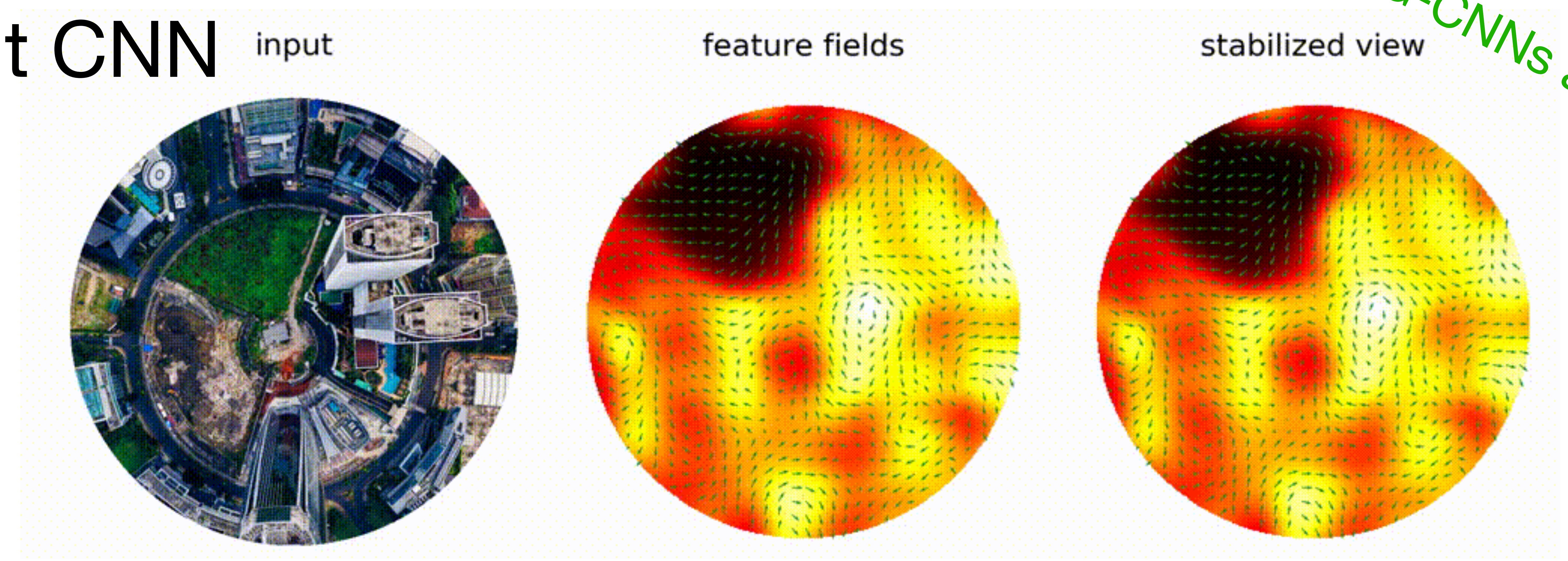
Geometric guarantees (equivariance)

Normal CNN



CNNs are not rotation equivariant

Group equivariant CNN



G-CNNs are rotation equivariant!

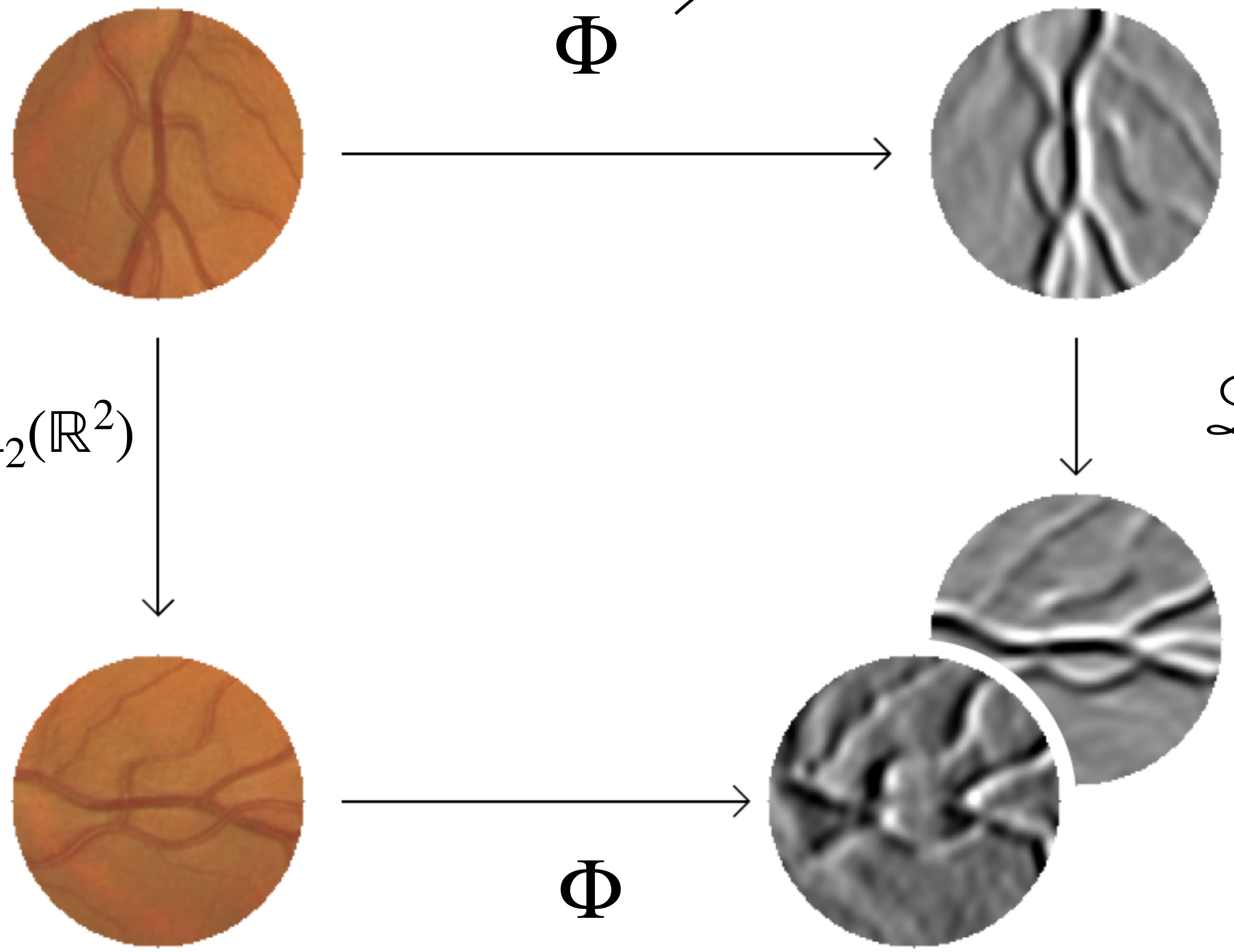
Figures source:
https://github.com/QUVA-Lab/e2cnn

Equivariance

Convolutions are generally **not equivariant to roto-translations**

$$(k \star_{\mathbb{R}^2} f)(\mathbf{x}) = (\mathscr{L}_{(\mathbf{x})}^{\mathbb{R}^2 \to \mathbb{L}_2(\mathbb{R}^2)} k \, , f)_{\mathbb{L}_2(\mathbb{R}^2)}$$

Representation of the translation group



$$\mathscr{L}_\theta^{SO(2) \to \mathbb{L}_2(\mathbb{R}^2)}$$

$$\mathscr{L}_g^{SO(2) \to \mathbb{L}_2(\mathbb{R}^2)}$$

Representation of the rotation group

SE(2) equivariant cross-correlations

Representation of the roto-translation group!

Lifting correlations: $(k \tilde{\star} f)(\mathbf{x}, \theta) = (\mathscr{L}_g^{SE(2)\to\mathbb{L}_2(\mathbb{R}^2)} k \, , f)_{\mathbb{L}_2(\mathbb{R}^2)}$

SE(2) equivariant cross-correlations

Representation of the roto-translation group!

Lifting correlations: $(k \tilde{\star} f)(\mathbf{x}, \theta) = (\mathscr{L}_g^{SE(2) \to \mathbb{L}_2(\mathbb{R}^2)} k\ , f)_{\mathbb{L}_2(\mathbb{R}^2)} = (\mathscr{L}_{\mathbf{x}}^{\mathbf{R}^2 \to \mathbb{L}_2(\mathbb{R}^2)} \mathscr{L}_{\theta}^{SO(2) \to \mathbb{L}_2(\mathbb{R}^2)} k\ , f)_{\mathbb{L}_2(\mathbb{R}^2)}$

translation *rotation*

SE(2) equivariant cross-correlations

Representation of the roto-translation group!

$k(\mathbf{R}_\theta^{-1}(\mathbf{x}'-\mathbf{x}))$

Lifting correlations: $(k \tilde{\star} f)(\mathbf{x}, \theta) = (\mathscr{L}_g^{SE(2)\to\mathbb{L}_2(\mathbb{R}^2)}\, k \,,\, f)_{\mathbb{L}_2(\mathbb{R}^2)} = (\overbrace{\mathscr{L}_{\mathbf{x}}^{\mathbf{R}^2\to\mathbb{L}_2(\mathbb{R}^2)}\, \mathscr{L}_\theta^{SO(2)\to\mathbb{L}_2(\mathbb{R}^2)}\, k}^{k(\mathbf{R}_\theta^{-1}(\mathbf{x}'-\mathbf{x}))} \,,\, f)_{\mathbb{L}_2(\mathbb{R}^2)}$

translation *rotation*

SE(2) equivariant cross-correlations

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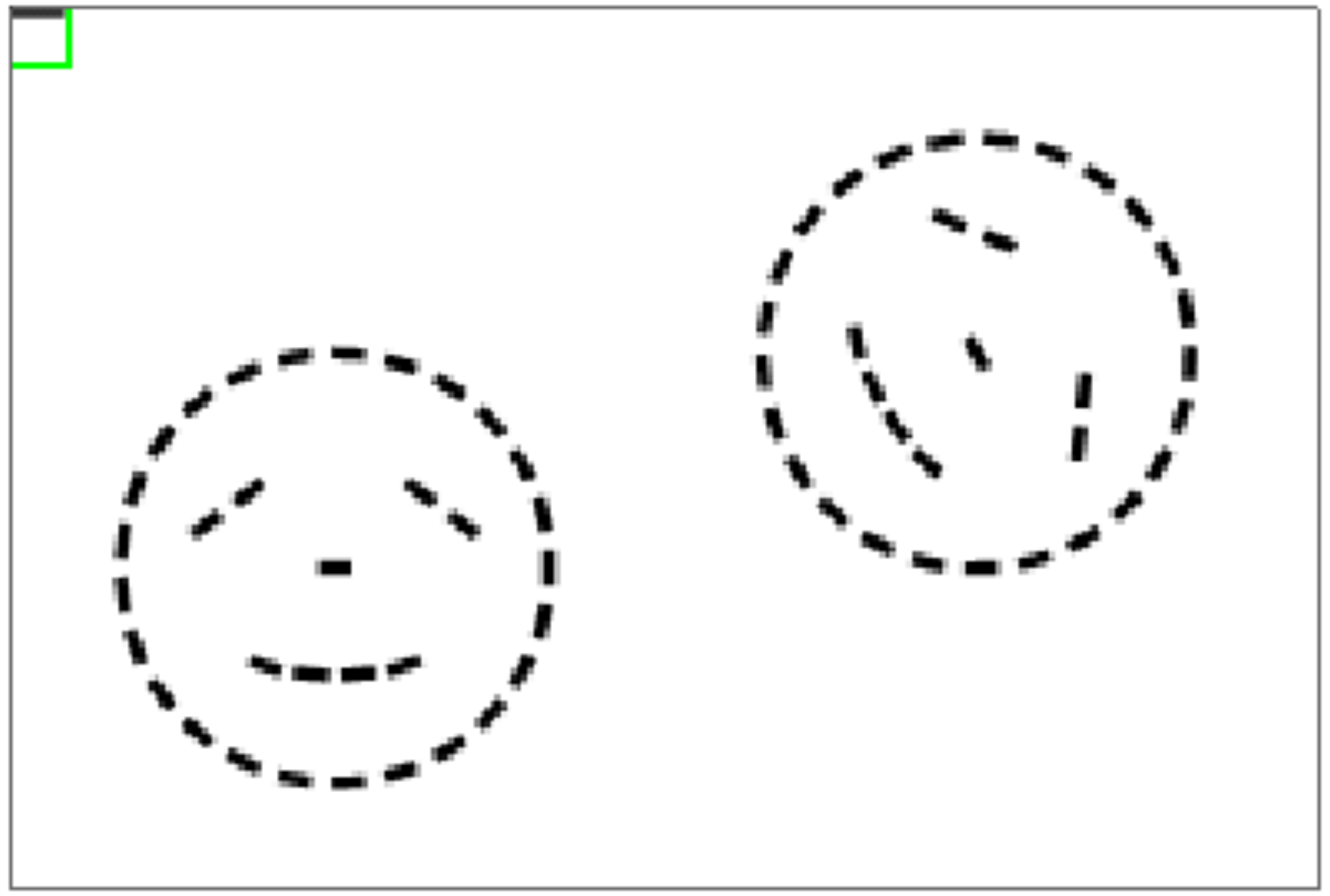
translation *rotation*

$\star_{\mathbb{R}^2}$



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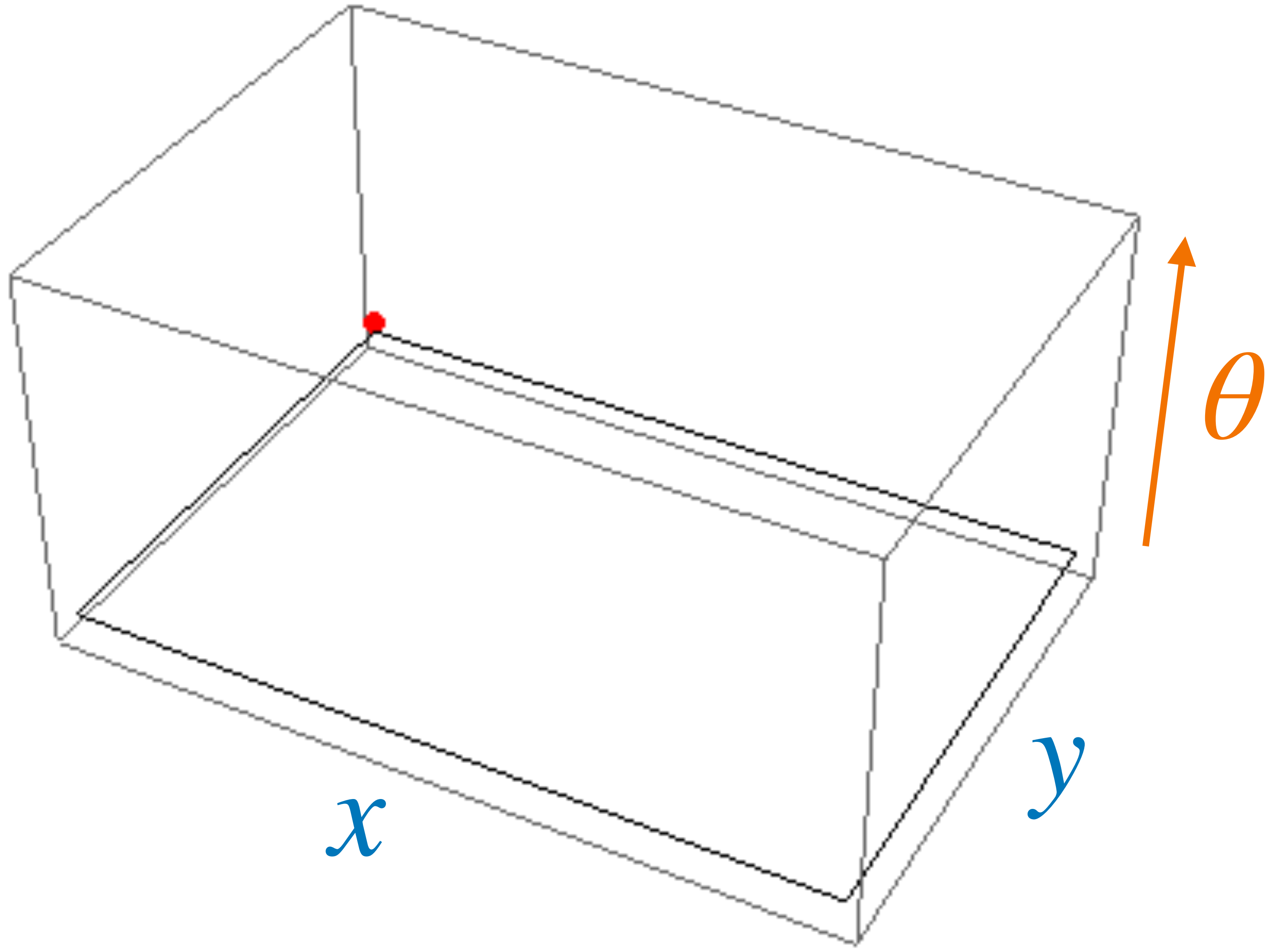


$\mathscr{L}_{\theta}^{SO(2)\rightarrow\mathbb{L}_2(\mathbb{R}^2)} k$
Rotated 2D convolution kernel

f^{in}
2D feature map

f^{out}
3D (*SE(2)*) feature map (after ReLU)

SE(2) equivariant cross-correlations

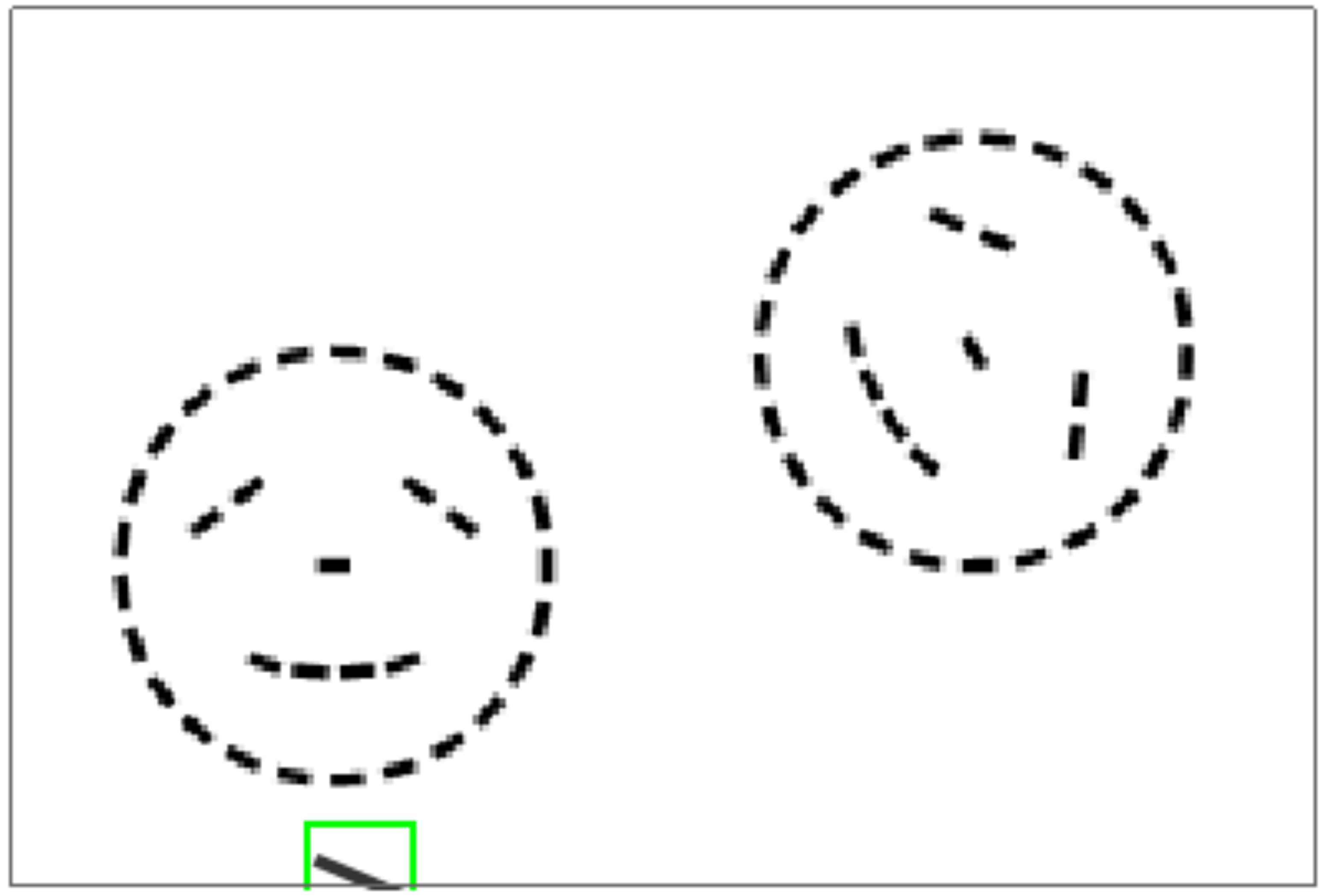
Representation of the roto-translation group!

$k(\mathbf{R}_\theta^{-1}(\mathbf{x}'-\mathbf{x}))$

Lifting correlations: $(k \tilde{\star} f)(\mathbf{x},\theta) = (\mathscr{L}_g^{SE(2)\to\mathbb{L}_2(\mathbb{R}^2)} k \, , f)_{\mathbb{L}_2(\mathbb{R}^2)} = (\overbrace{\mathscr{L}_{\mathbf{x}}^{\mathbb{R}^2\to\mathbb{L}_2(\mathbb{R}^2)} \mathscr{L}_\theta^{SO(2)\to\mathbb{L}_2(\mathbb{R}^2)} k}^{k(\mathbf{R}_\theta^{-1}(\mathbf{x}'-\mathbf{x}))} \, , f)_{\mathbb{L}_2(\mathbb{R}^2)}$

translation *rotation*

$\star_{\mathbb{R}^2}$



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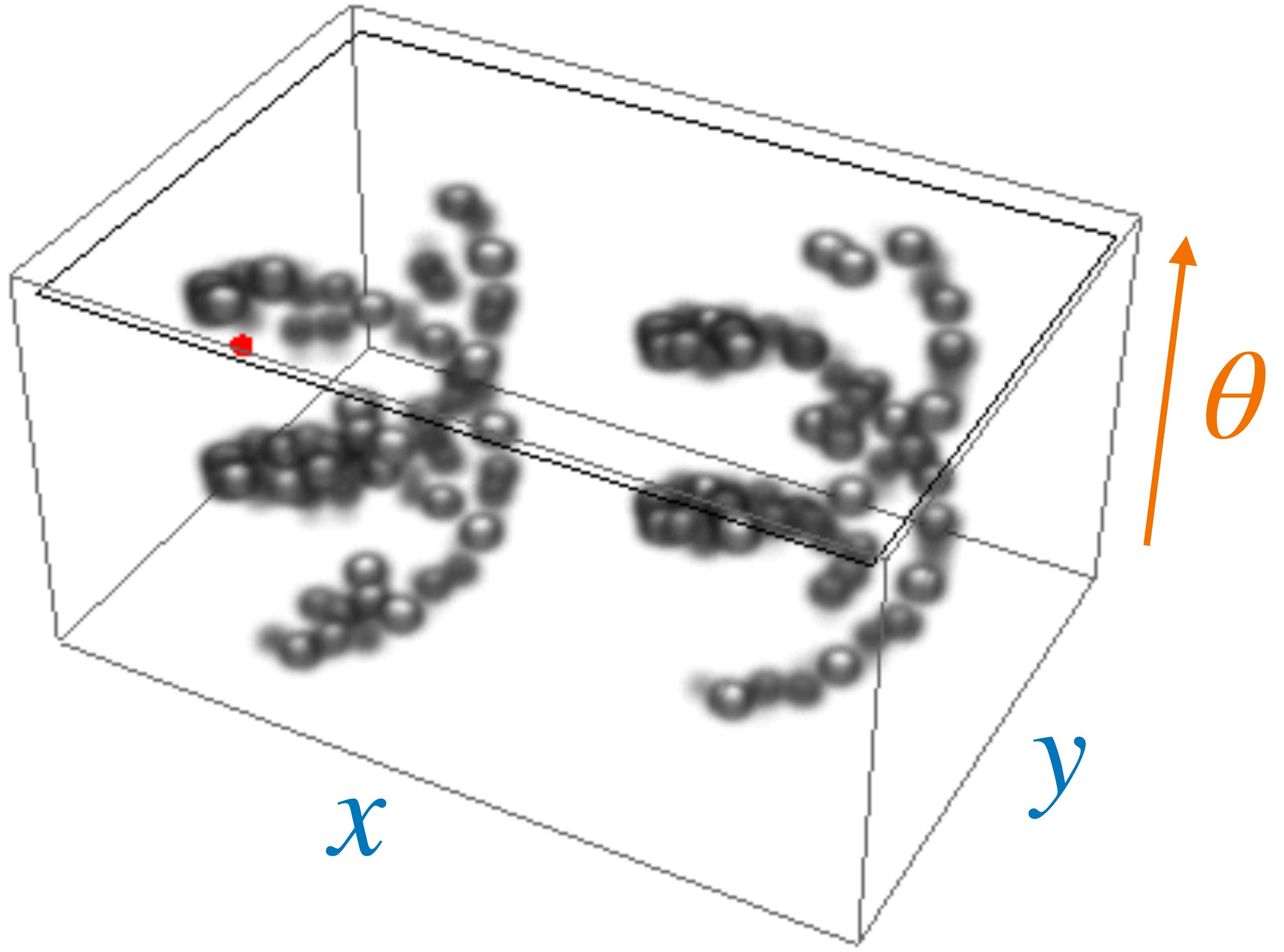


$\mathscr{L}_\theta^{SO(2)\to\mathbb{L}_2(\mathbb{R}^2)} k$

Rotated 2D convolution kernel

f^{in}

2D feature map

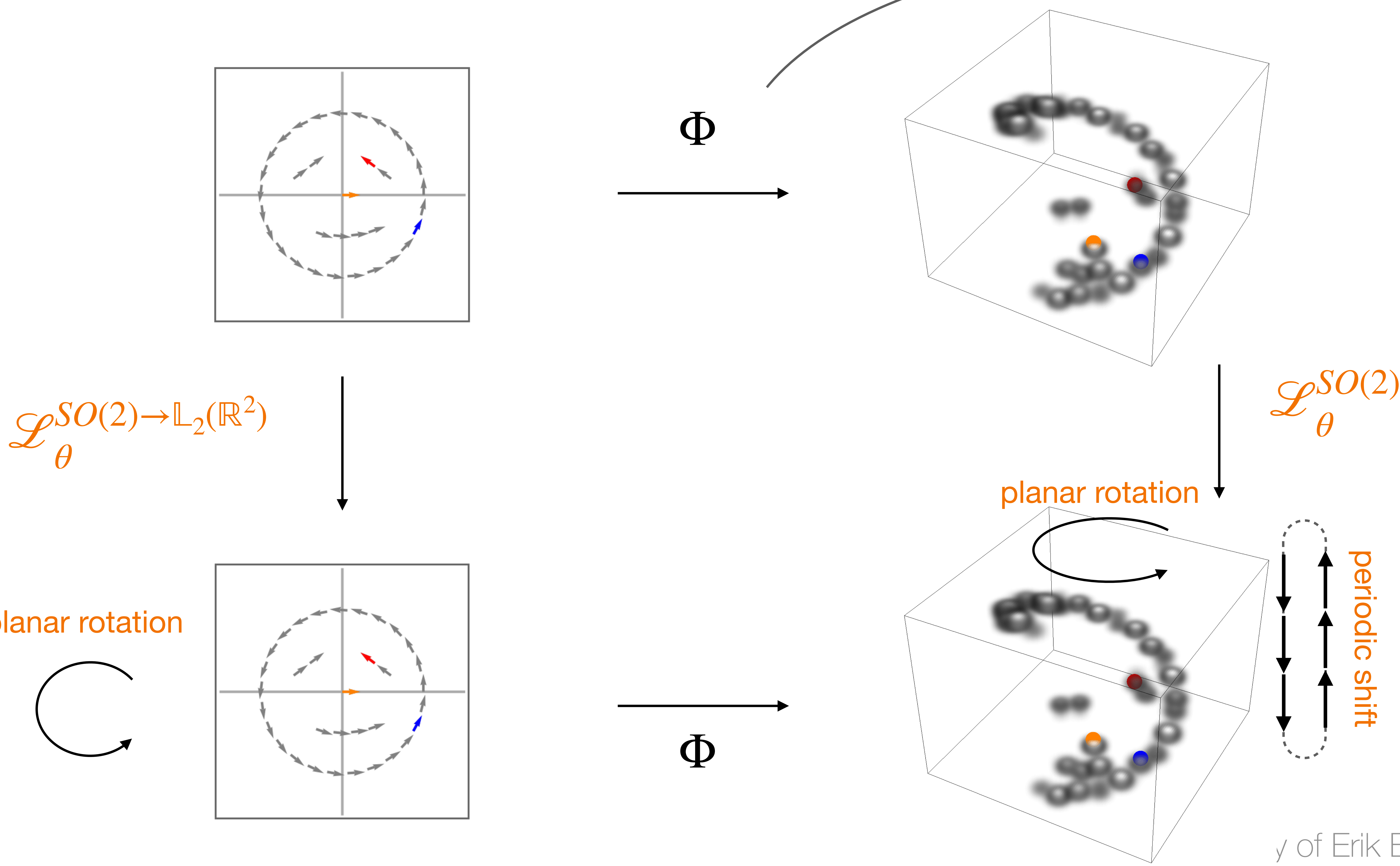
f^{out}

3D (*SE(2)*) feature map (after ReLU)

Equivariance

SE(2) group **lifting convolutions** are roto-translation equivariant

$$(k \tilde{\star} f)(\mathbf{x}, \theta) = (\mathscr{L}_{\mathbf{x}}^{\mathbf{R}^2 \to \mathbb{L}_2(\mathbb{R}^2)} \mathscr{L}_{\theta}^{SO(2) \to \mathbb{L}_2(\mathbb{R}^2)} k \, , f)_{\mathbb{L}_2(\mathbb{R}^2)}$$



Equivariance

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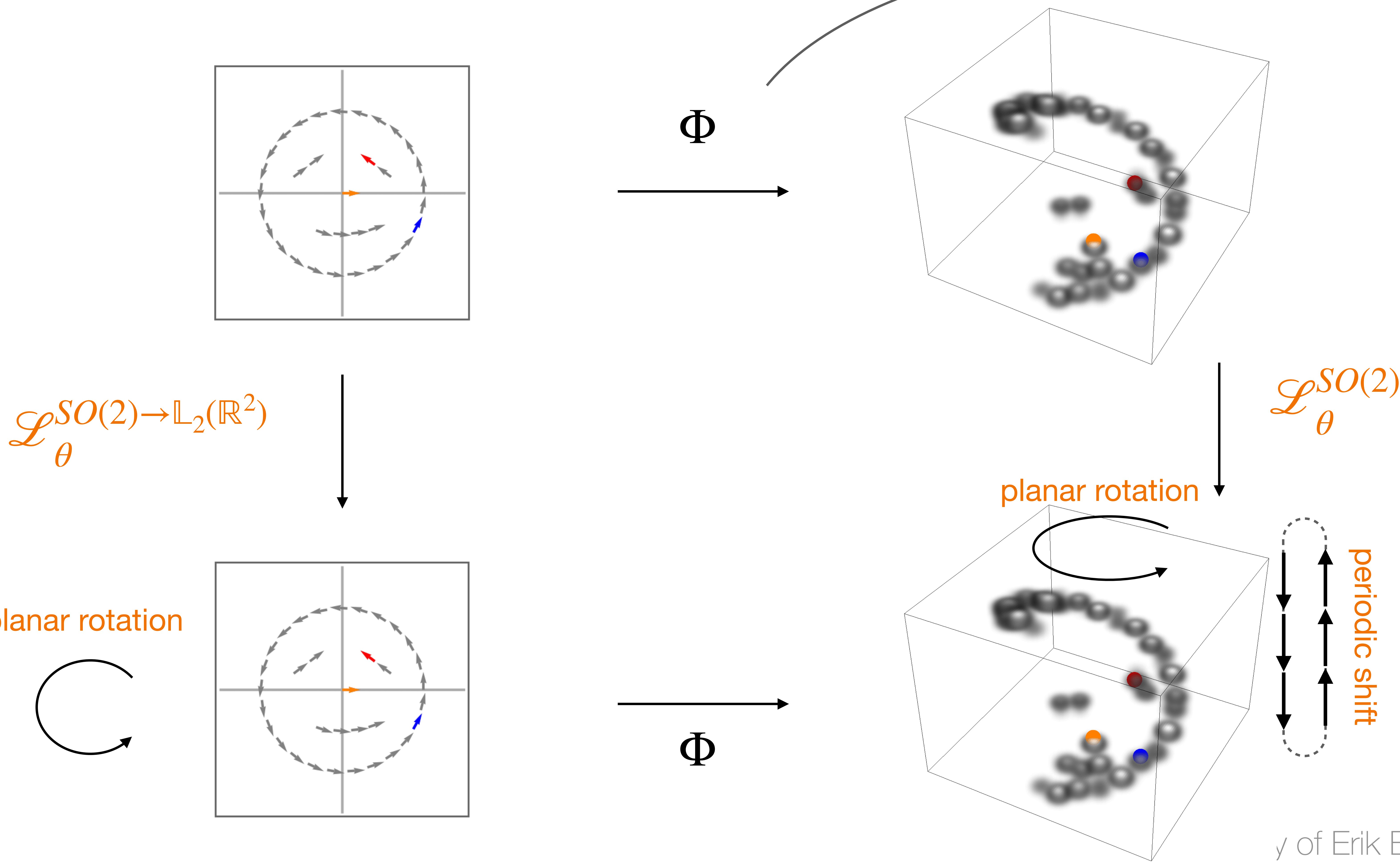
$$(k \tilde{\star} f)(\mathbf{x}, \theta) = (\mathscr{L}_{\mathbf{x}}^{\mathbf{R}^2 \to \mathbb{L}_2(\mathbb{R}^2)} \mathscr{L}_{\theta}^{SO(2) \to \mathbb{L}_2(\mathbb{R}^2)} k \ , f)_{\mathbb{L}_2(\mathbb{R}^2)}$$



Equivariance

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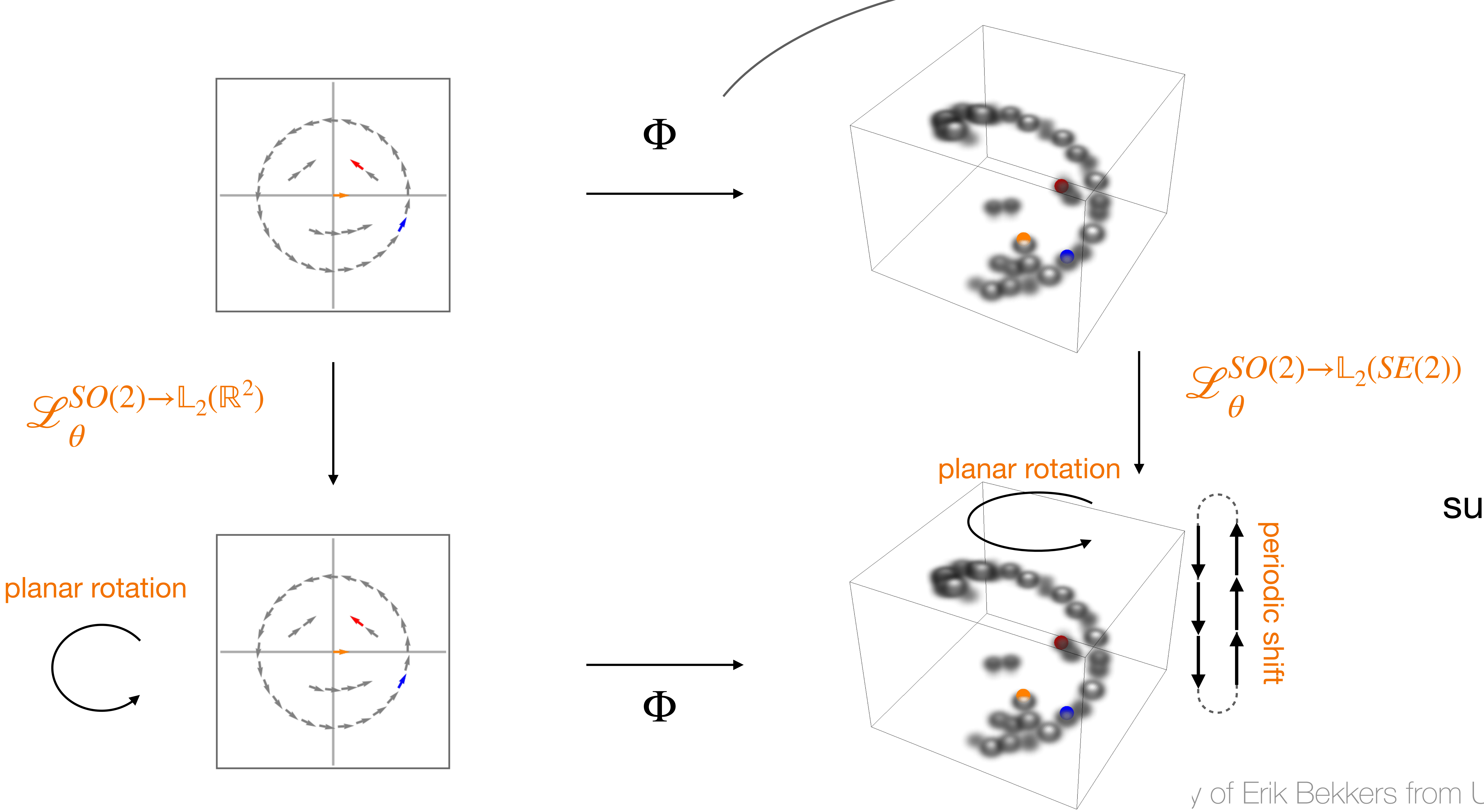
$$(k \,\tilde{\star}\, f)(\mathbf{x},\theta) = (\mathscr{L}_{\mathbf{x}}^{\mathbf{R}^2\to\mathbb{L}_2(\mathbb{R}^2)}\mathscr{L}_{\theta}^{SO(2)\to\mathbb{L}_2(\mathbb{R}^2)}\, k\;,\, f)_{\mathbb{L}_2(\mathbb{R}^2)}$$



What about subsequent layers?

SE(2) equivariant cross-correlations

Group correlations:

$$(k \star f)(\mathbf{x}, \theta) = (\mathscr{L}_g^{SE(2)\to\mathbb{L}_2(SE(2))}\, k \;, f)_{\mathbb{L}_2(SE(2))} = (\overbrace{\mathscr{L}_{\mathbf{x}}^{\mathbf{R}^2\to\mathbb{L}_2(SE(2))}\, \mathscr{L}_{\theta}^{SO(2)\to\mathbb{L}_2(SE(2))}\, k}^{k(\mathbf{R}_\theta^{-1}(\mathbf{x}'-\mathbf{x}),\mathbf{R}_{\theta'-\theta})} \;, f)_{\mathbb{L}_2(SE(2)}$$

translation *rotation*

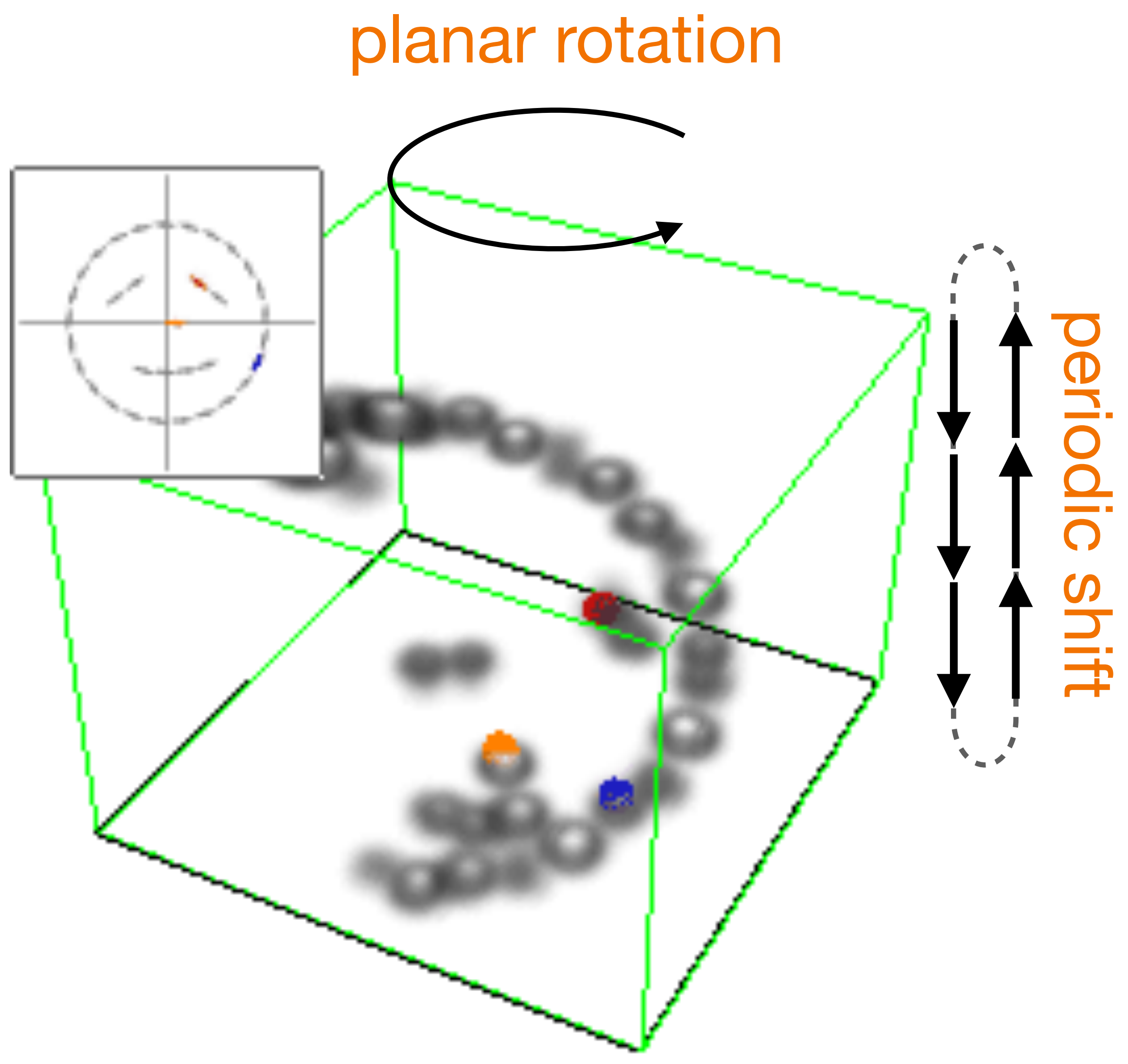
SE(2) equivariant cross-correlations

$k(\mathbf{R}_\theta^{-1}(\mathbf{x}'-\mathbf{x}),\mathbf{R}_{\theta'-\theta})$

Group correlations:

$$(k \star f)(\mathbf{x},\theta) = (\mathscr{L}_g^{SE(2)\to\mathbb{L}_2(SE(2))}\, k\, ,\, f)_{\mathbb{L}_2(SE(2))} = (\overbrace{\mathscr{L}_{\mathbf{x}}^{\mathbf{R}^2\to\mathbb{L}_2(SE(2))}\,\mathscr{L}_\theta^{SO(2)\to\mathbb{L}_2(SE(2))}\, k}\, ,\, f)_{\mathbb{L}_2(SE(2)}$$

translation *rotation*



$\mathscr{L}_\theta^{SO(2)\to\mathbb{L}_2(SE(2)} k$

Rotated SE(2) convolution kernel

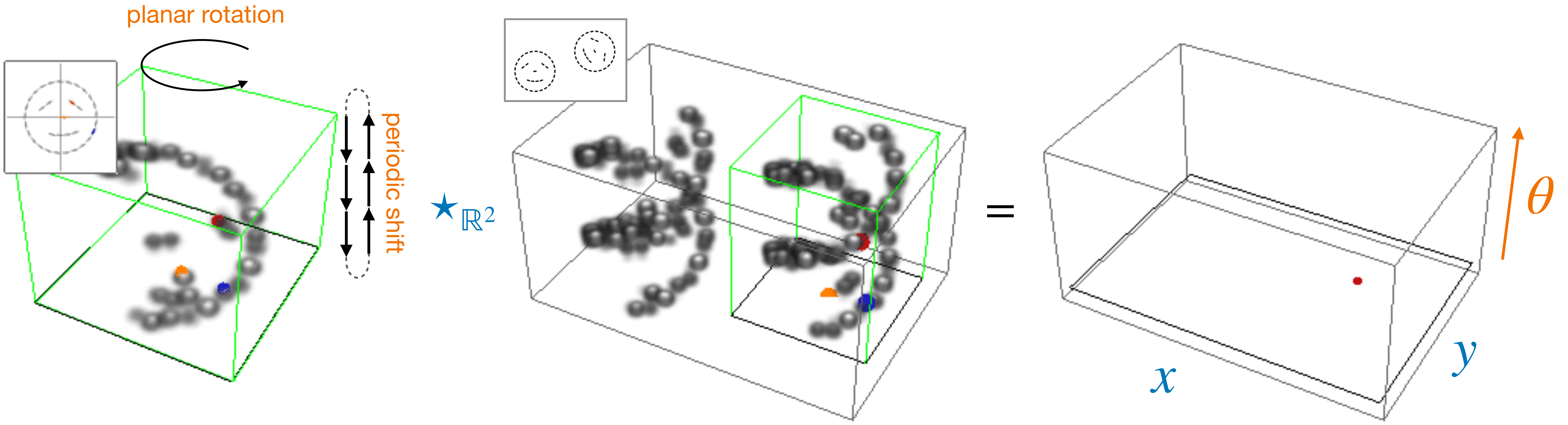
Slide curtesy of Erik Bekkers from UVA Deep Learning II Course

SE(2) equivariant cross-correlations

Group correlations:

$$(k \star f)(\mathbf{x},\theta) = (\mathscr{L}_g^{SE(2)\to\mathbb{L}_2(SE(2))}\, k\ ,\, f)_{\mathbb{L}_2(SE(2))} = (\overbrace{\mathscr{L}_{\mathbf{x}}^{\mathbf{R}^2\to\mathbb{L}_2(SE(2))}\,\mathscr{L}_\theta^{SO(2)\to\mathbb{L}_2(SE(2))}\, k}^{k(\mathbf{R}_\theta^{-1}(\mathbf{x}'-\mathbf{x}),\mathbf{R}_{\theta'-\theta})}\ ,\, f)_{\mathbb{L}_2(SE(2)}$$

translation *rotation*



$\mathscr{L}_\theta^{SO(2)\to\mathbb{L}_2(SE(2)}k$

Rotated SE(2) convolution kernel

f^{in}

SE(2) feature map

f^{out}

SE(2) feature map (after ReLU)

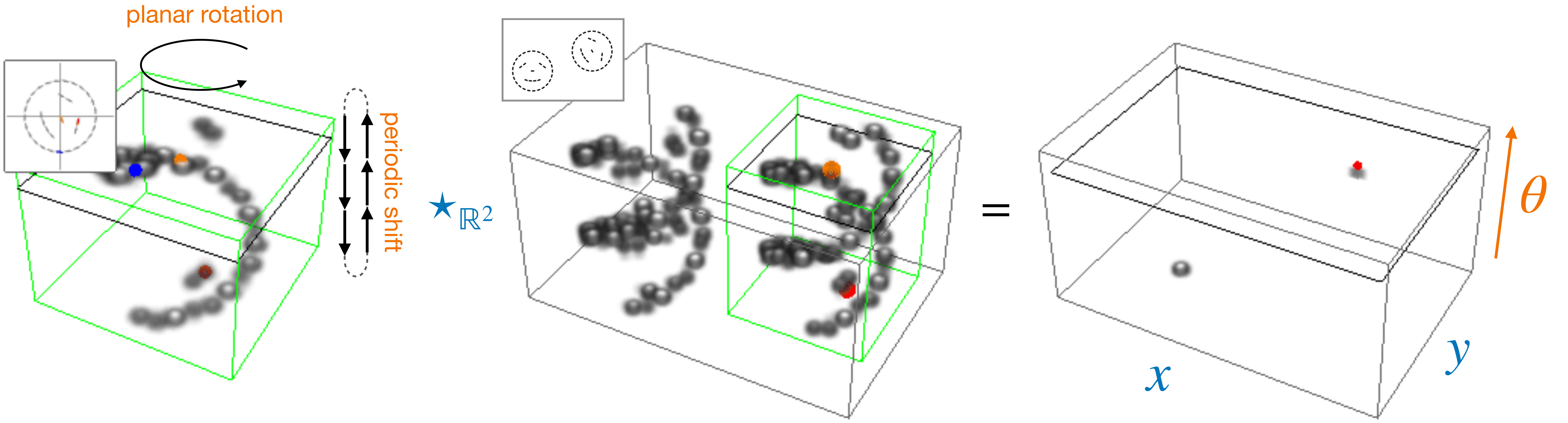
Slide curtesy of Erik Bekkers from UVA Deep Learning II Course

SE(2) equivariant cross-correlations

Group correlations:

$$(k \star f)(\mathbf{x},\theta) = (\mathscr{L}_g^{SE(2)\to\mathbb{L}_2(SE(2))}\, k\,,\, f)_{\mathbb{L}_2(SE(2))} = (\overbrace{\mathscr{L}_{\mathbf{x}}^{\mathbf{R}^2\to\mathbb{L}_2(SE(2))}\,\mathscr{L}_\theta^{SO(2)\to\mathbb{L}_2(SE(2))}\, k}^{k(\mathbf{R}_\theta^{-1}(\mathbf{x}'-\mathbf{x}),\mathbf{R}_{\theta'-\theta})}\,,\, f)_{\mathbb{L}_2(SE(2)}$$

translation *rotation*



$\mathscr{L}_\theta^{SO(2)\to\mathbb{L}_2(SE(2)}k$

Rotated SE(2) convolution kernel

f^{in}

SE(2) feature map

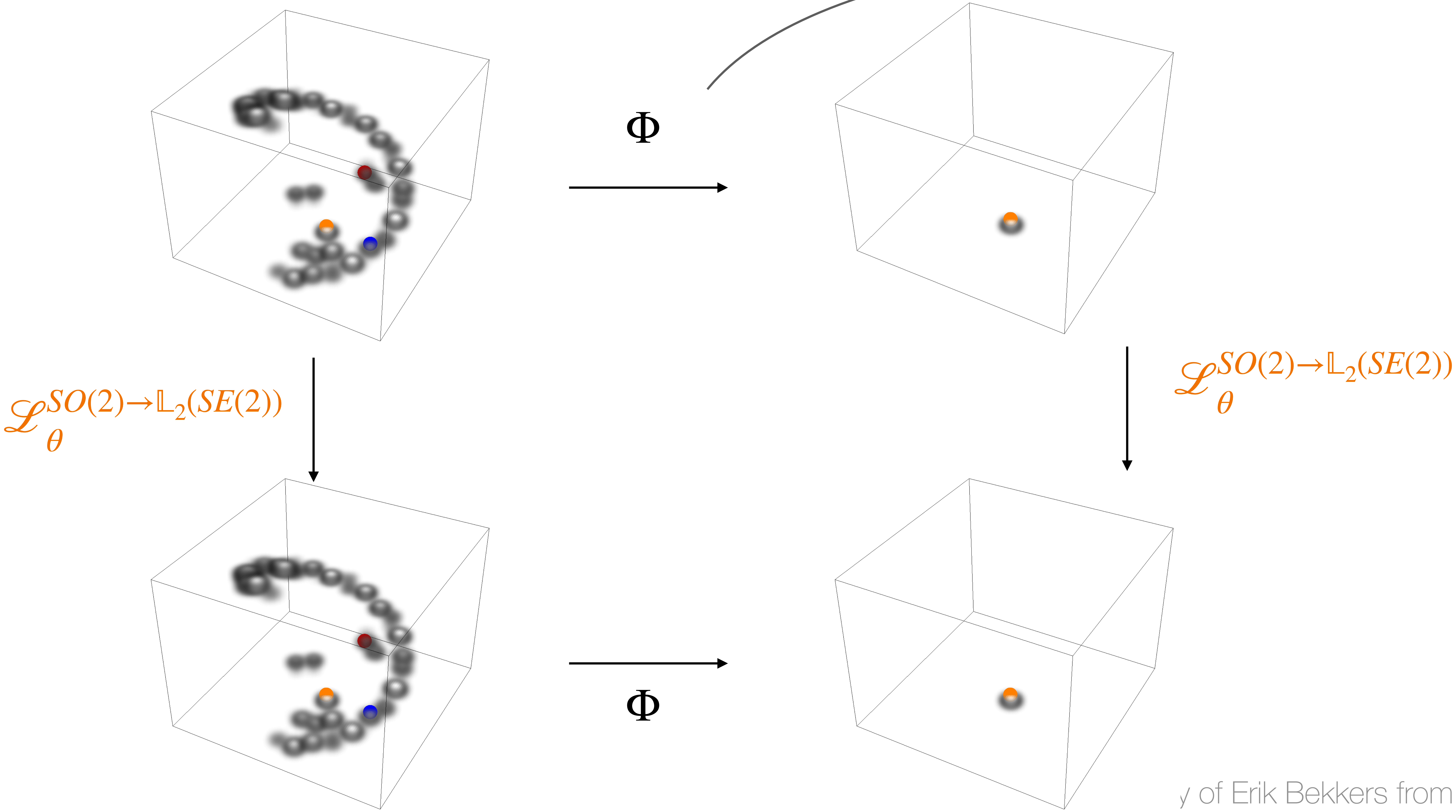
f^{out}

SE(2) feature map (after ReLU)

Equivariance

SE(2) group convolutions are roto-translation equivariant

$$(k \star f)(\mathbf{x}, \theta) = (\mathscr{L}_{\mathbf{x}}^{\mathbb{R}^2 \to \mathbb{L}_2(SE(2))} \mathscr{L}_{\theta}^{SO(2) \to \mathbb{L}_2(SE(2))} k \, , f)_{\mathbb{L}_2(SE(2))}$$



Equivariance

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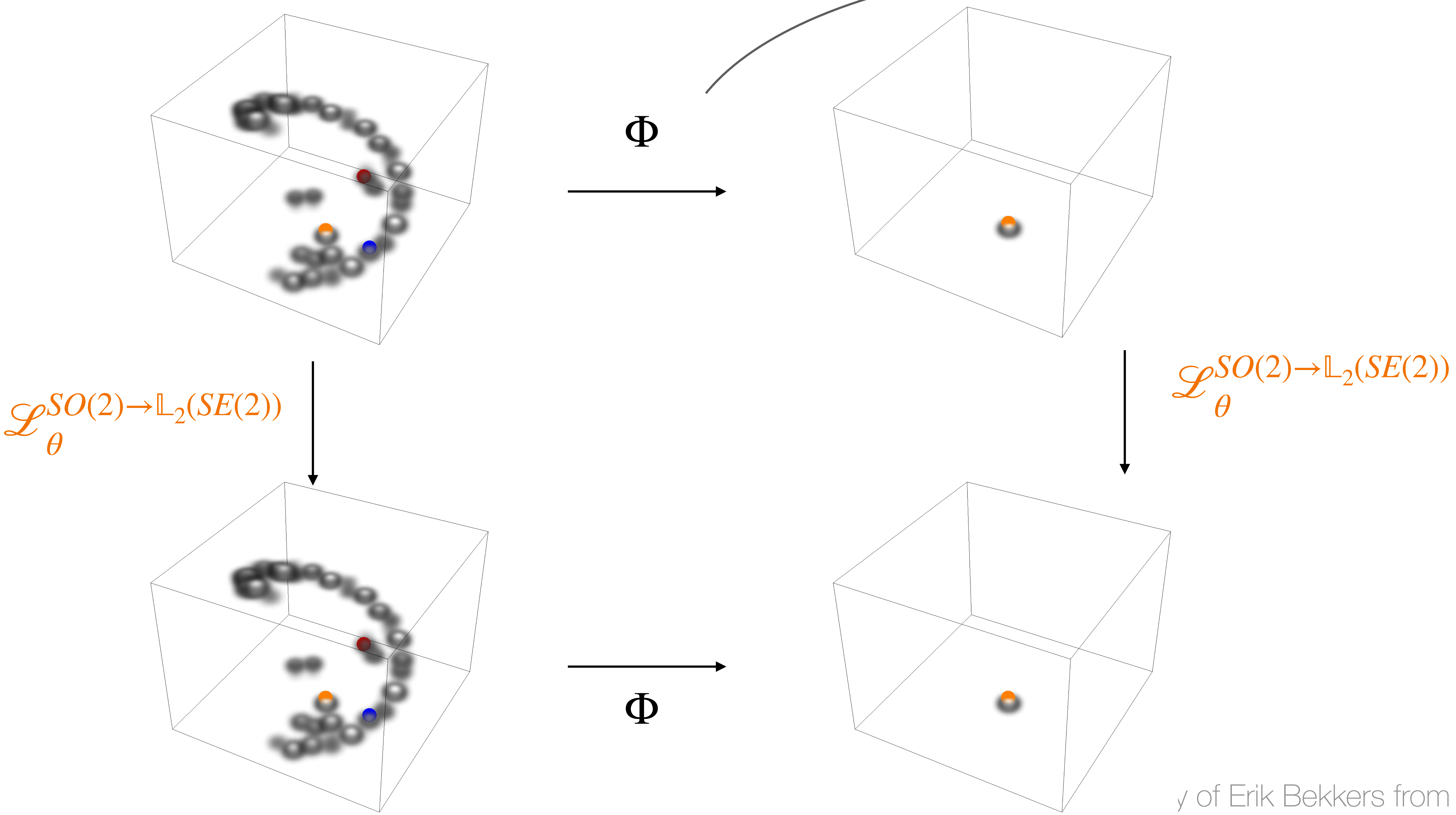
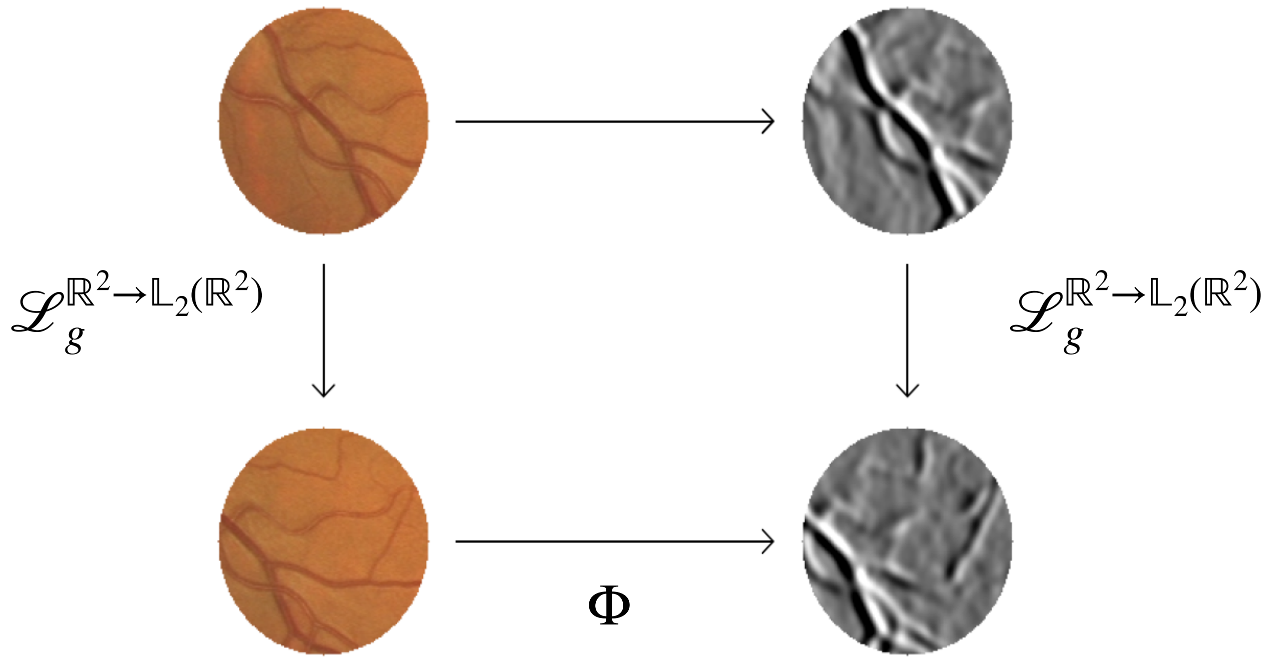


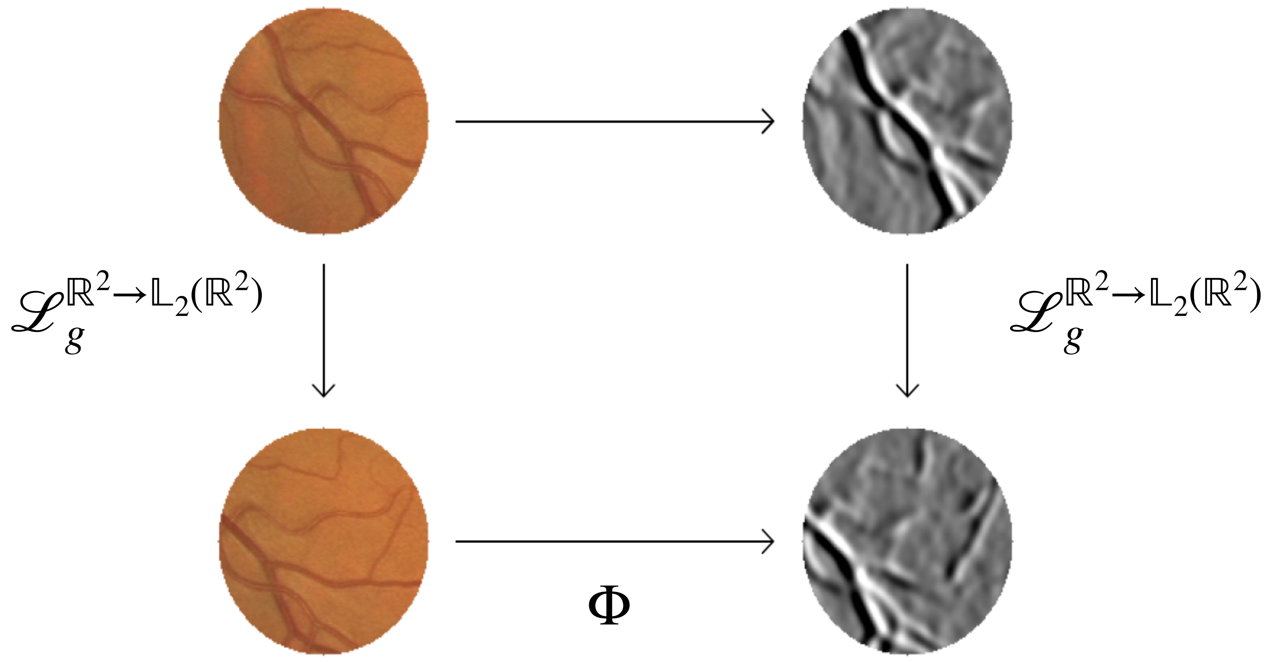
2D cross-correlation (translation equivariant)



$$(k \star_{\mathbb{R}^2} f)(\mathbf{x}) = (\mathscr{L}_{\mathbf{x}}^{\mathbb{R}^2 \to \mathbb{L}_2(\mathbb{R}^2))} k, f)_{\mathbb{L}_2(\mathbb{R}^2)}$$

$$= \int_{\mathbb{R}^2} k(\mathbf{x}' - \mathbf{x}) f(\mathbf{x}') d\mathbf{x}'$$

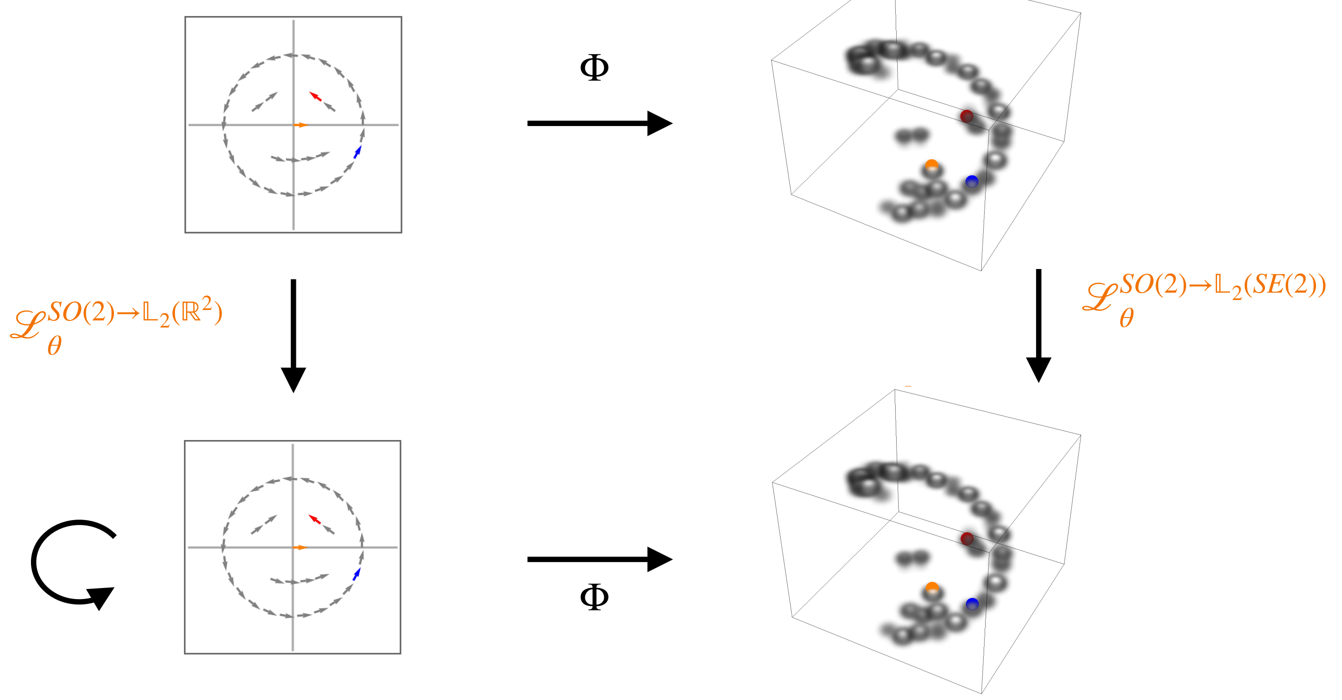
2D cross-correlation (translation equivariant)



$$(k \star_{\mathbb{R}^2} f)(\mathbf{x}) = (\mathcal{L}_{\mathbf{x}}^{\mathbb{R}^2\to\mathbb{L}_2(\mathbb{R}^2))} k, f)_{\mathbb{L}_2(\mathbb{R}^2)}$$

$$= \int_{\mathbb{R}^2} k(\mathbf{x}' - \mathbf{x}) f(\mathbf{x}') d\mathbf{x}'$$

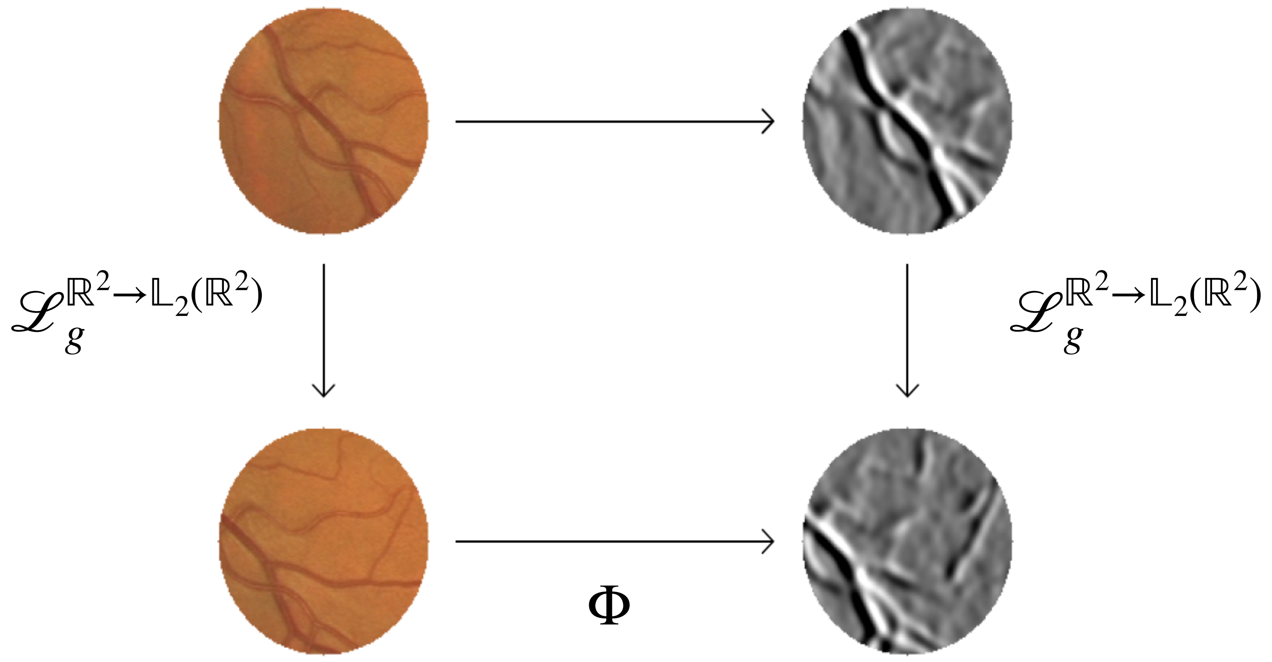
SE(2) lifting correlations (roto-translation equivariant)



$$(k \tilde{\star} f)(\mathbf{x}, \theta) = (\mathcal{L}_g^{SE(2)\to\mathbb{L}_2(\mathbb{R}^2)}\, k\, , f)_{\mathbb{L}_2(\mathbb{R}^2)}$$

$$= \int_{\mathbb{R}^2} k(\mathbf{R}_\theta^{-1}(\mathbf{x}' - \mathbf{x})) f(\mathbf{x}') d\mathbf{x}'$$

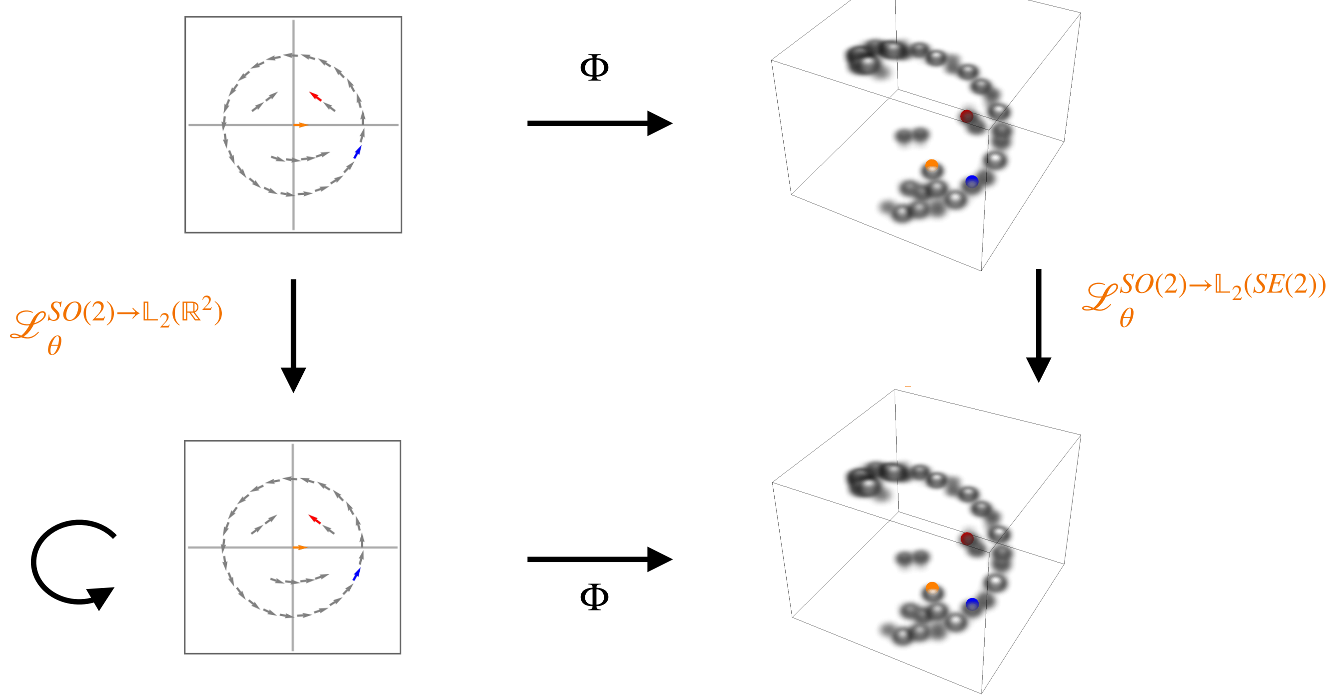
2D cross-correlation (translation equivariant)



$$(k \star_{\mathbb{R}^2} f)(\mathbf{x}) = (\mathcal{L}_{\mathbf{x}}^{\mathbb{R}^2\to\mathbb{L}_2(\mathbb{R}^2)} k, f)_{\mathbb{L}_2(\mathbb{R}^2)}$$

$$= \int_{\mathbb{R}^2} k(\mathbf{x}' - \mathbf{x}) f(\mathbf{x}') d\mathbf{x}'$$

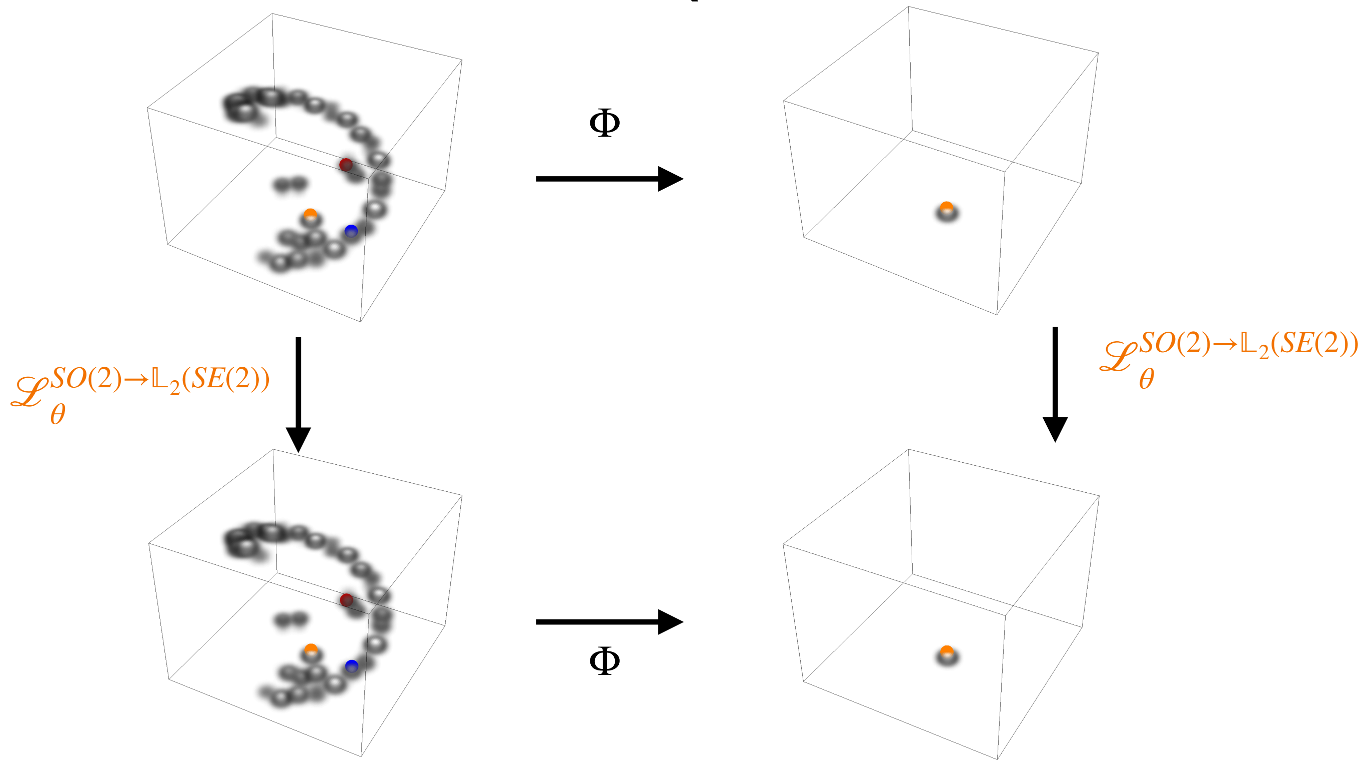
SE(2) lifting correlations (roto-translation equivariant)



$$(k \,\tilde{\star}\, f)(\mathbf{x}, \theta) = (\mathcal{L}_g^{SE(2)\to\mathbb{L}_2(\mathbb{R}^2)}\, k\,, f)_{\mathbb{L}_2(\mathbb{R}^2)}$$

$$= \int_{\mathbb{R}^2} k(\mathbf{R}_\theta^{-1}(\mathbf{x}' - \mathbf{x})) f(\mathbf{x}') d\mathbf{x}'$$

SE(2) G-correlations (roto-translation equivariant)



$$(k \,\tilde{\star}\, f)(\mathbf{x}, \theta) = (\mathcal{L}_g^{SE(2)\to\mathbb{L}_2(SE(2))}\, k\,, f)_{\mathbb{L}_2(SE(2))}$$

$$= \int_{\mathbb{R}^2}\int_{S^1} k(\mathbf{R}_\theta^{-1}(\mathbf{x}' - \mathbf{x}), \theta' - \theta \mod 2\pi) f(\mathbf{x}', \theta') d\mathbf{x}' d\theta'$$

Discussion

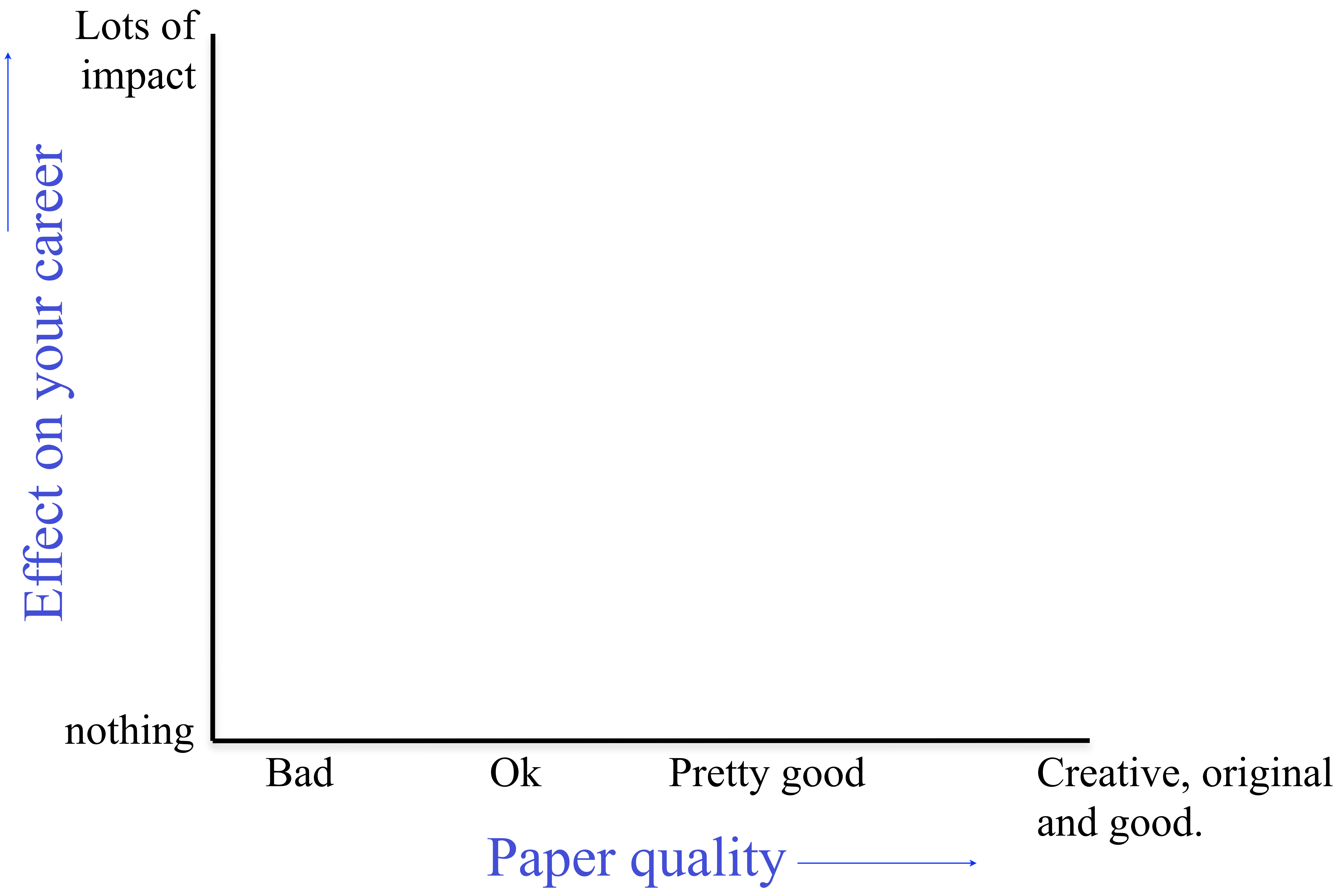
- Geometric Deep Learning and Group Convolutions are great in theory
- In practice, obviously, they are similarly useful: See MLP vs. CNN.
- However, for groups *other* than the translation group, it is *not obvious* that we want perfect equivariance.
- Group convolutions can become expensive b/c of combinatorial growth of feature maps: *for each translation* $\times$ *for each scale* $\times$ *for each rotation* $\times$ *…*
- Nevertheless, there are clear and apparent use-cases - which we will see in the paper session :)

How to write papers & How to give talks

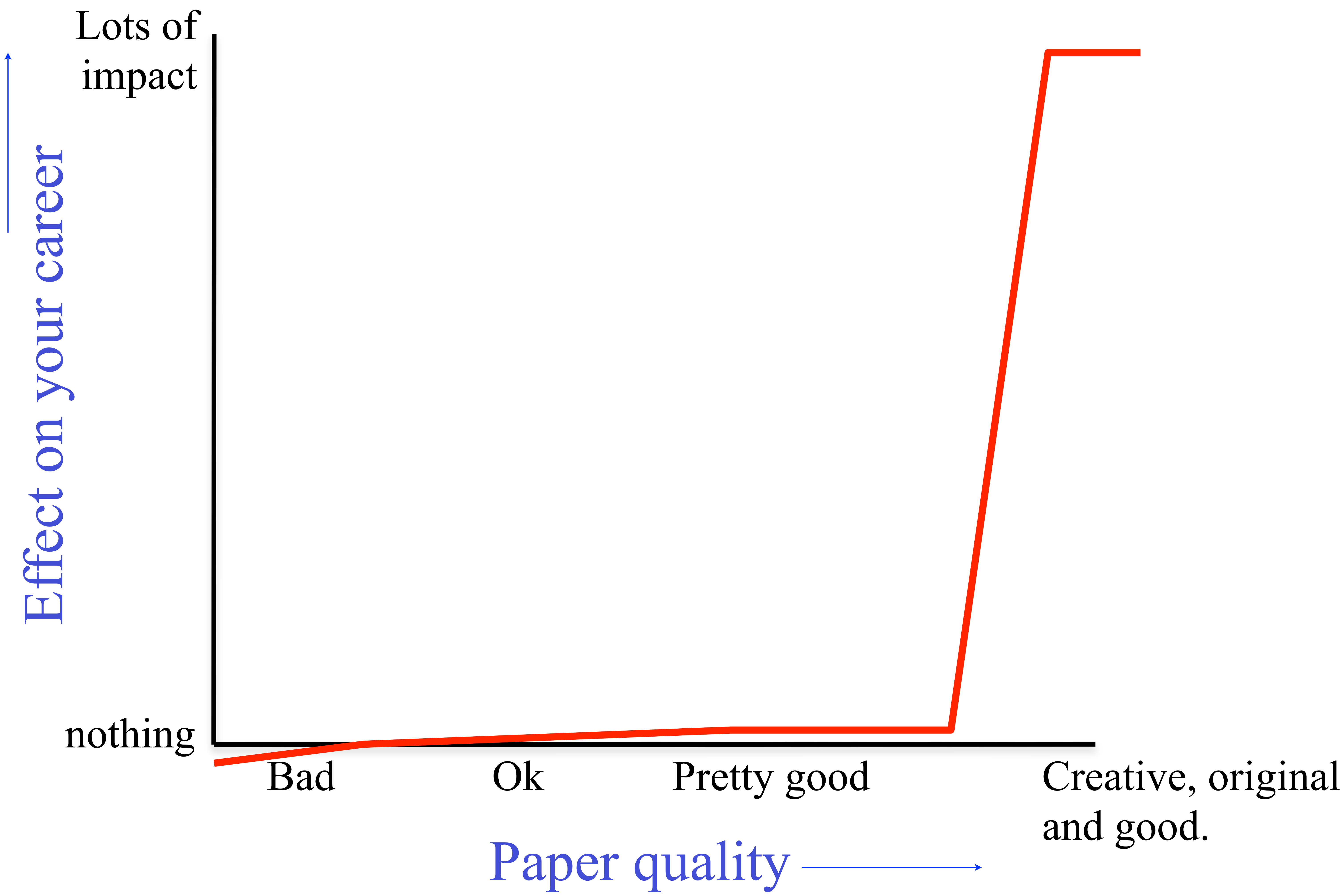
Outline

- writing technical papers
- giving technical talks

A paper's impact on your career

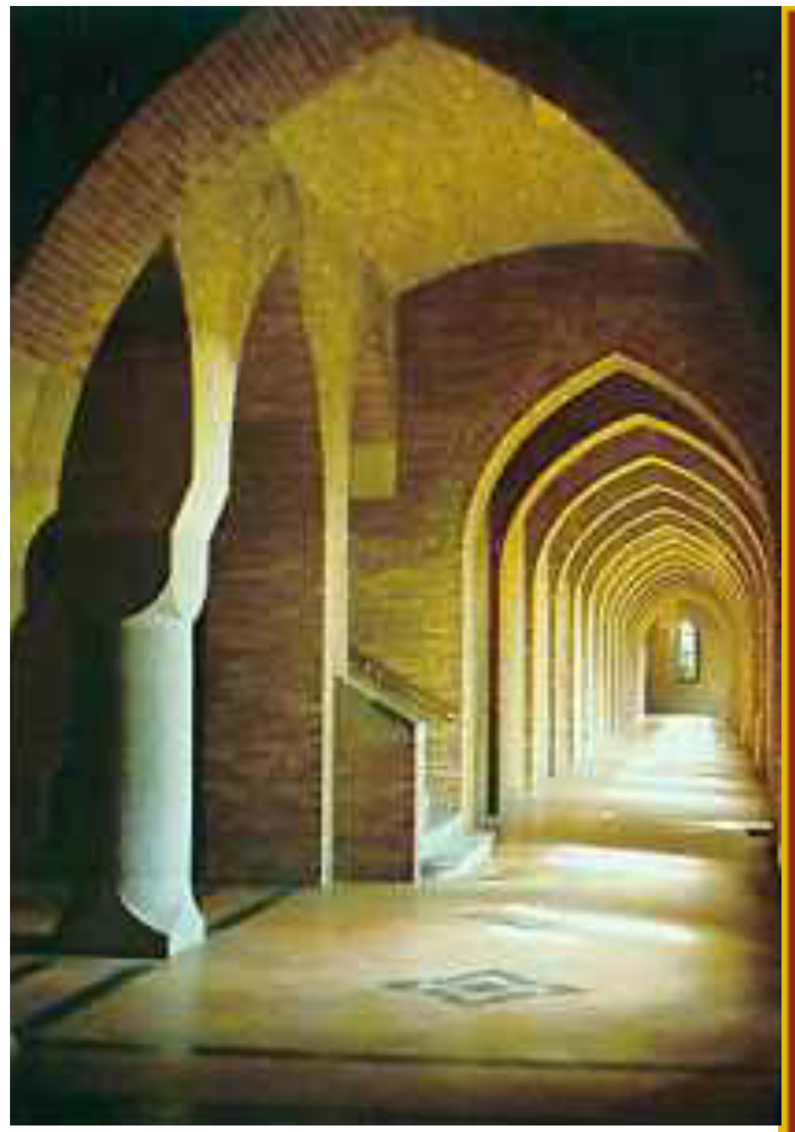


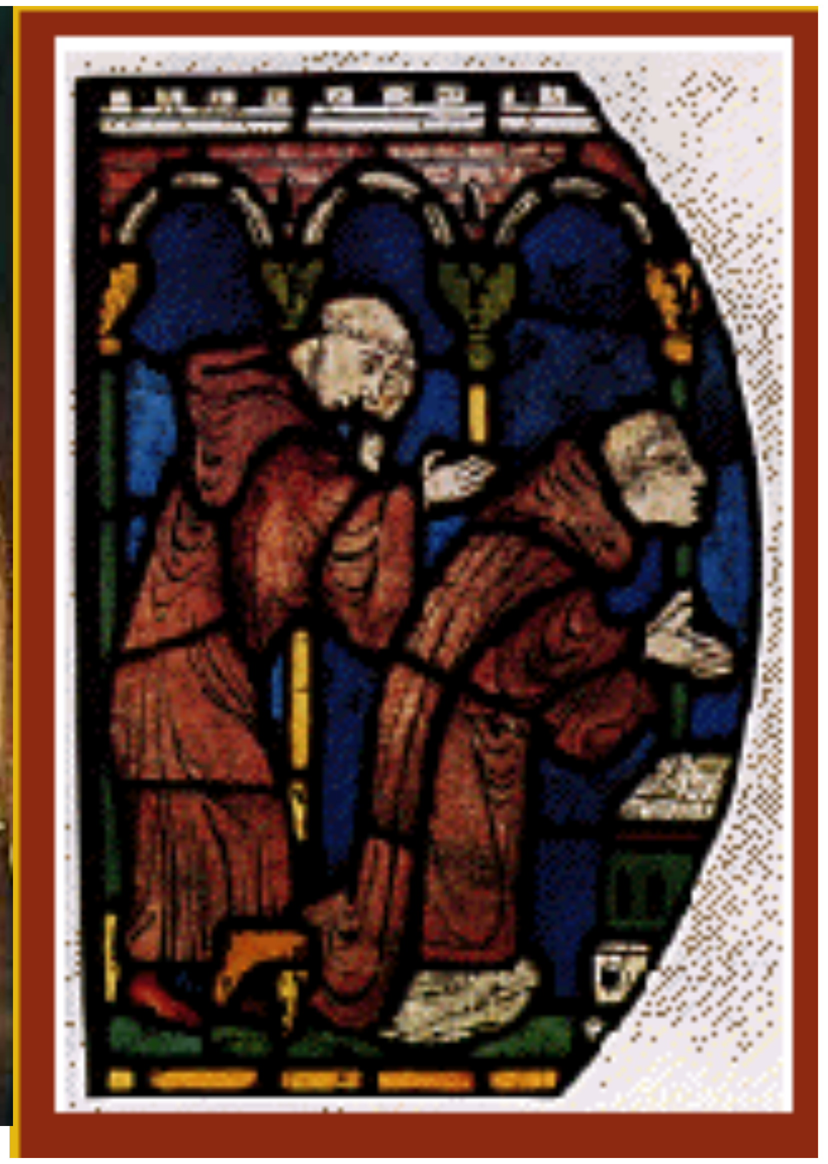
A paper’s impact on your career

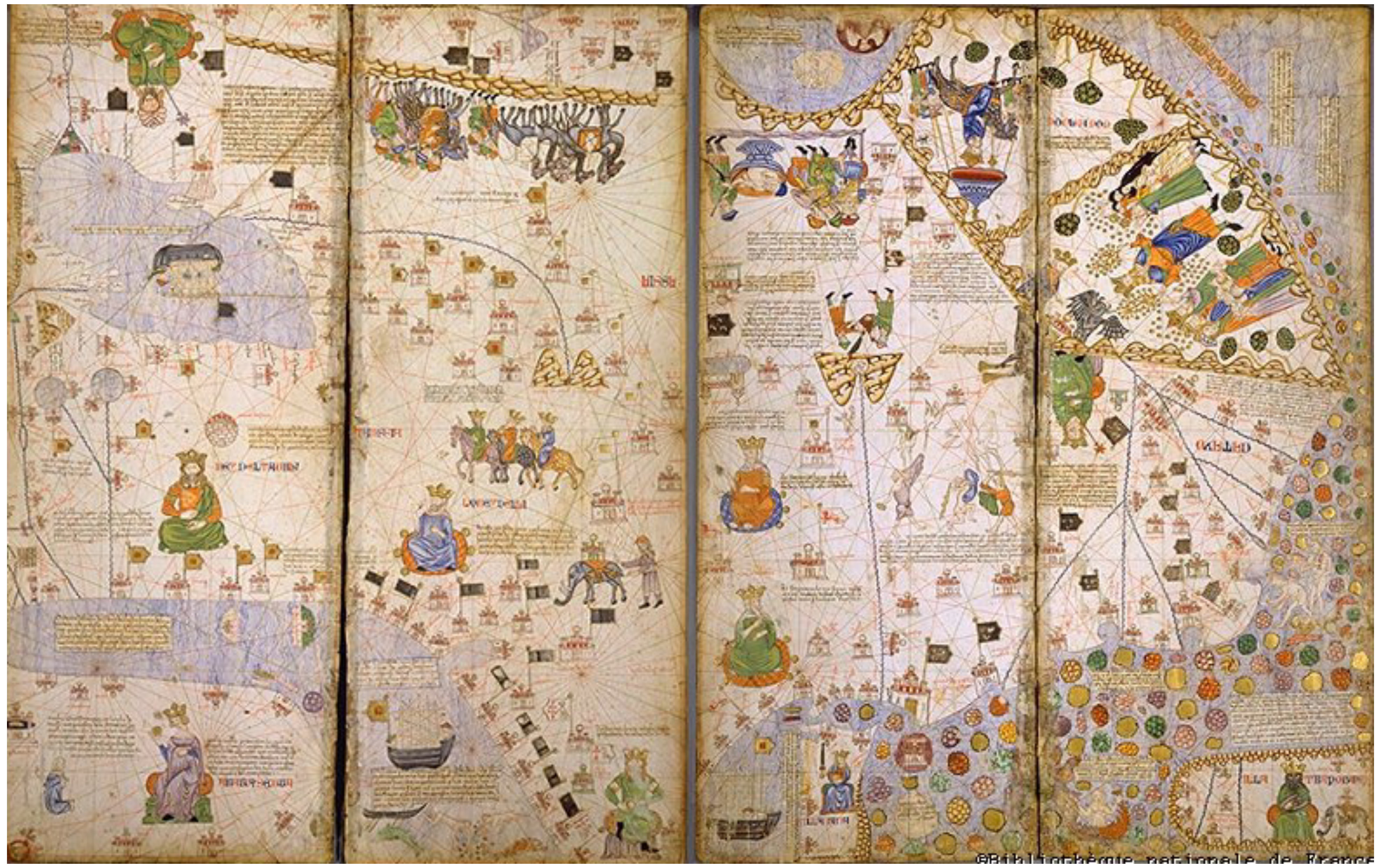


Our image of the research community

- Scholars, plenty of time on their hands, pouring over your manuscript.







The reality:
more like a large, crowded marketplace

http://ducksflytogether.wordpress.com/2008/08/02/looking-back-khan-el-khalili/

The (abridged) Heilmeier Catechism

George H. Heilmeier, former DARPA director (1975-1977)

- Problem definition: What are you trying to do?
- How is it done today, and what are the limits of current practice?
- What is your approach and why is it better?
- Who cares? If you are successful, what difference will it make?
- What are the mid-term and final “exams” to check for success?

Ted Adelson on how to write a good paper

1. Start by stating which problem you are addressing, keeping the audience in mind. They must care about it, which means that sometimes you must tell them why they should care about the problem.
2. Then state briefly what the other solutions are to the problem, and why they aren't satisfactory. If they were satisfactory, you wouldn't need to do the work.
3. Then explain your own solution, compare it with other solutions, and say why it's better.
4. At the end, talk about related work where similar techniques and experiments have been used, but applied to a different problem.
5. Since I developed this formula, it seems that all the papers I've written have been accepted. (told informally, in conversation, 1990).

Example paper organization:
removing camera shake from a single photograph

1 Introduction

2 Related work

3 Image model

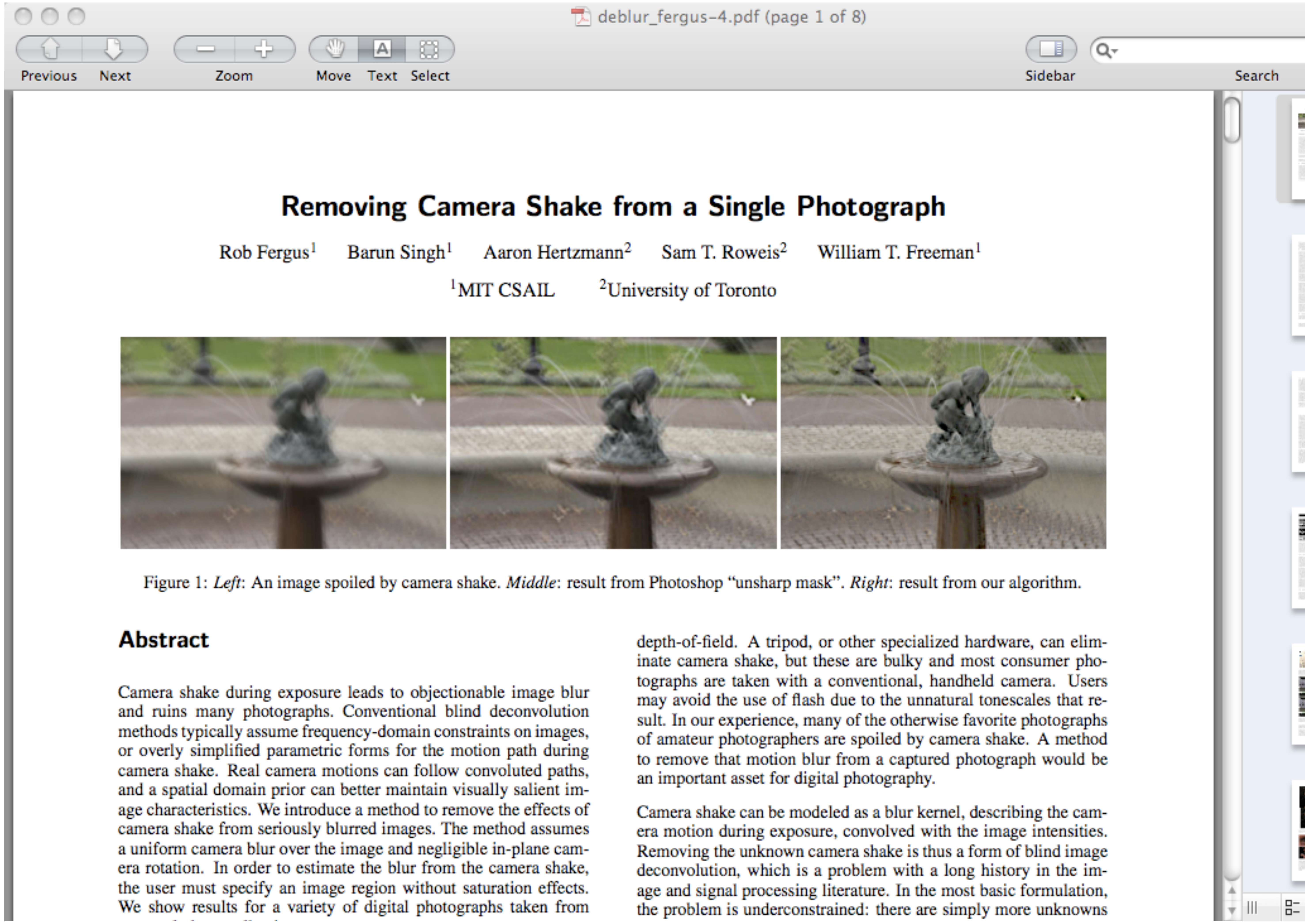
4 Algorithm

- Estimating the blur kernel
  - Multi-scale approach
  - User supervision
- Image reconstruction

5 Experiments

- Small blurs
- Large blurs
- Images with significant saturation

6 Discussion



Removing Camera Shake from a Single Photograph

Rob Fergus[1] Barun Singh[1] Aaron Hertzmann[2] Sam T. Roweis[2] William T. Freeman[1]

[1]MIT CSAIL [2]University of Toronto

Figure 1: *Left*: An image spoiled by camera shake. *Middle*: result from Photoshop "unsharp mask". *Right*: result from our algorithm.

Abstract

Camera shake during exposure leads to objectionable image blur and ruins many photographs. Conventional blind deconvolution methods typically assume frequency-domain constraints on images, or overly simplified parametric forms for the motion path during camera shake. Real camera motions can follow convoluted paths, and a spatial domain prior can better maintain visually salient image characteristics. We introduce a method to remove the effects of camera shake from seriously blurred images. The method assumes a uniform camera blur over the image and negligible in-plane camera rotation. In order to estimate the blur from the camera shake, the user must specify an image region without saturation effects. We show results for a variety of digital photographs taken from

depth-of-field. A tripod, or other specialized hardware, can eliminate camera shake, but these are bulky and most consumer photographs are taken with a conventional, handheld camera. Users may avoid the use of flash due to the unnatural tonescales that result. In our experience, many of the otherwise favorite photographs of amateur photographers are spoiled by camera shake. A method to remove that motion blur from a captured photograph would be an important asset for digital photography.

Camera shake can be modeled as a blur kernel, describing the camera motion during exposure, convolved with the image intensities. Removing the unknown camera shake is thus a form of blind image deconvolution, which is a problem with a long history in the image and signal processing literature. In the most basic formulation, the problem is underconstrained: there are simply more unknowns

The introduction

1 Introduction
2 Related work
3 --Main idea--
4 Algorithm
- Estimating the blur kernel
    - Multi-scale approach
    - User supervision
- Image reconstruction

5 Experiments
- Small blurs
- Large blurs
- Images with significant saturation

6 Discussion

Jim Kajiya: write a dynamite introduction

(The guy who developed the rendering equation)

You must make your paper easy to read. You've got to make it easy for anyone to tell what your paper is about, what problem it solves, why the problem is interesting, what is really new in your paper (and what isn't), why it's so neat. And you must do it up front. In other words, you must write a dynamite introduction.

Underutilized technique: explain the main idea with a simple, toy example.

1 Introduction
2 Related work
3 Main idea
4 Algorithm
    Estimating the blur kernel
        Multi-scale approach
        User supervision
    Image reconstruction
5 Experiments
    Small blurs
    Large blurs
    Images with significant saturation
6 Discussion

Often useful here.

Show simple toy examples to let people get the main idea

From "Shiftable multiscale transforms"

Two different signals to be represented—both have the same shape, but one is by 1 pixel relative to the other.

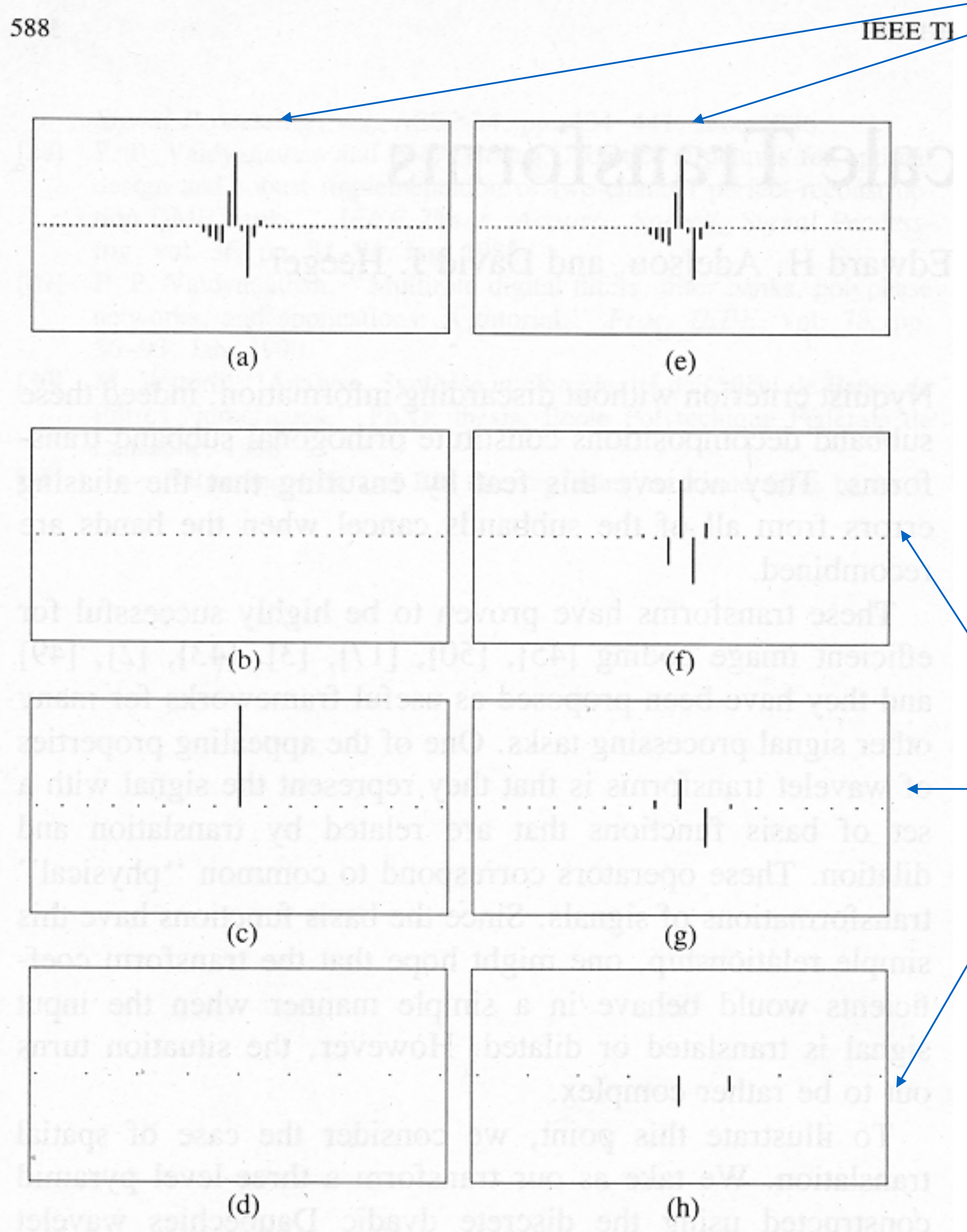


Fig. 1. Effect of translation on the wavelet representation of a signal. (a) Input signal, which is equal to one of the wavelet basis functions. (b)–(d) Decomposition of the signal into three wavelet subbands. Plotted are the coefficients of each subband. Dots correspond to zero-value coefficients. (e) Same input signal, translated one sample to to the right. (f)–(h) Decomposition of the shifted signal into three wavelet subbands. Note the drastic change in the coefficients of the transform, both within and between subbands.

Three different frequency bands of the resulting wavelet representations. Note the big change in the signal representation caused by shifting it by 1 pixel!

Experimental results are critical now at CVPR

1 Introduction
2 Related work
3 Image model
4 Algorithm
    Estimating the blur kernel
        Multi-scale approach
        User supervision
    Image reconstruction
5 Experiments
    Small blurs
    Large blurs
    Images with significant saturation
6 Discussion

Gone are the days of, "We think this is a great idea and we expect it will be very useful in computer vision. See how it works on this meaningless, contrived problem?"

Experimental results are critical now at CVPR

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6 Discussion

Methods	Dataset	two-view?	**si-full**	**si-env**	**si-hum**	**si-intra**	**si-inter**	**RMSE**	**Rel**
Russell *et al.* [31]	-	Yes	2.146	2.021	2.207	2.206	2.093	2.520	0.772
DeMoN [39]	RGBD+MVS	Yes	0.338	0.302	0.360	0.293	0.384	0.866	0.220
Chen *et al.* [3]	NYU+DIW	No	0.441	0.398	0.458	0.408	0.470	1.004	0.262
Laina *et al.* [17]	NYU	No	0.358	0.356	0.349	0.270	0.377	0.947	0.223
Xu *et al.* [46]	NYU	No	0.427	0.419	0.411	0.302	0.451	1.085	0.274
Fu *et al.* [7]	NYU	No	0.351	0.357	0.334	0.257	0.360	0.925	0.194
I	MC	No	0.318	0.334	0.294	0.227	0.319	0.840	0.204
$IFCM$	MC	Yes	0.316	0.330	0.302	0.228	0.323	0.843	0.206
$ID_{pp}M$	MC	Yes	0.246	0.225	0.260	0.233	0.273	0.635	0.136
$ID_{pp}CM$ (w/o d. cleaning)	MC	Yes	0.272	0.238	0.293	0.258	0.282	0.688	0.147
$ID_{pp}CM$	MC	Yes	0.232	0.203	0.252	0.224	0.262	0.570	0.129
$ID_{pp}CMK$	MC	Yes	**0.221**	**0.195**	**0.238**	**0.215**	**0.247**	**0.541**	**0.125**

Table 2. **Results on TUM RGBD datasets.** Different si-RMSE metrics as well as standard RMSE and relative error (Rel) are reported. We evaluate our models (light gray background) under different input configurations, as described in Table 1. *w/o d. cleaning* indicates the model is trained using raw MVS depth predictions as supervision, without our depth cleaning method. Dataset '-' indicates the method is not learning based. Lower is better for all error metrics.

Gone are the days of, "We think this is a great idea and we expect it will be very useful in computer vision. See how it works on this meaningless, contrived problem?"

How to end a paper

1 Introduction

2 Related work

3 Image model

4 Algorithm

- Estimating the blur kernel
  - Multi-scale approach
  - User supervision
- Image reconstruction

5 Experiments

- Small blurs
- Large blurs
- Images with significant saturation

6 Discussion

Conclusions, or what this opens up, or how this can change how we approach computer vision problems.

How not to end a paper

1 Introduction
2 Related work
3 Image model
4 Algorithm
  Estimating the blur kernel
    Multi-scale approach
    User supervision
  Image reconstruction
5 Experiments
  Small blurs
  Large blurs
  Images with saturation
6 Discussion
7 Future work?

I can't stand "future work" sections. It's hard to think of a weaker way to end a paper.

"Here's a list all the ideas we wanted to do but couldn't get to work in time for the conference submission deadline. We didn't do any of the following things: (1)… (2)…"

(You get no "partial credit" from reviewers and readers for neat things you wanted to do, but didn't.)

"Here's a list of good ideas that you should now go and do before we get a chance."

Better: to end with a conclusion or a summary, or you can say in general terms where the work may lead.

General writing tips

Knuth: keep the reader upper-most in your mind.

Perhaps the most important principle of good writing is to keep the reader uppermost in mind: What does the reader know so far? What does the reader expect next and why?

Treat the reader as you would a guest in your house

Anticipate their needs: would you like something to drink? Something to eat? Perhaps now, after eating, you'd like to rest?

Writing style, from the elements of style, Stunk and White

13. **Omit needless words.**

Vigorous writing is concise. A sentence should contain no unnecessary words, a paragraph no unnecessary sentences, for the same reason that a drawing should have no unnecessary lines and a machine no unnecessary parts. This requires not that the writer make all his sentences short, or that he avoid all detail and treat his subjects only in outline, but that every word tell.

Many expressions in common use violate this principle:

the question as to whether	whether (the question whether)
there is no doubt but that	no doubt (doubtless)
used for fuel purposes	used for fuel
he is a man who	he
in a hasty manner	hastily
this is a subject which	this subject
His story is a strange one.	His story is strange.

Re-writing exercise

The underlying assumption of this work is that the estimate of a given node will only depend on nodes within a patch: this is a locality assumption imposed at the patch-level. This assumption can be justified in case of skin images since a pixel in one corner of the image is likely to have small effect on a different pixel far away from itself. Therefore, we can crop the image into smaller windows, as shown in Figure 5, and compute the inverse J matrix of the cropped window. Since the cropped window is much smaller than the input image, the inversion of J matrix is computationally cheaper. Since we are inferring on blocks of image patches (i.e. ignoring pixels outside of the cropped window), the interpolated image will have blocky artifacts. Therefore, only part of xMAP is used to interpolate the image, as shown in Figure 5.

Before

We assume local influence--that nodes only depend on other nodes within a patch. This condition often holds for skin images, which have few long edges or structures. We crop the image into small windows, as shown in Fig. 5, and compute the inverse J matrix of each small window. This is much faster than computing the inverse J matrix for the input image. To avoid artifacts from the block processing, only the center region of xMAP is used in the final image, as shown in Fig. 5.

After

Re-writing exercise

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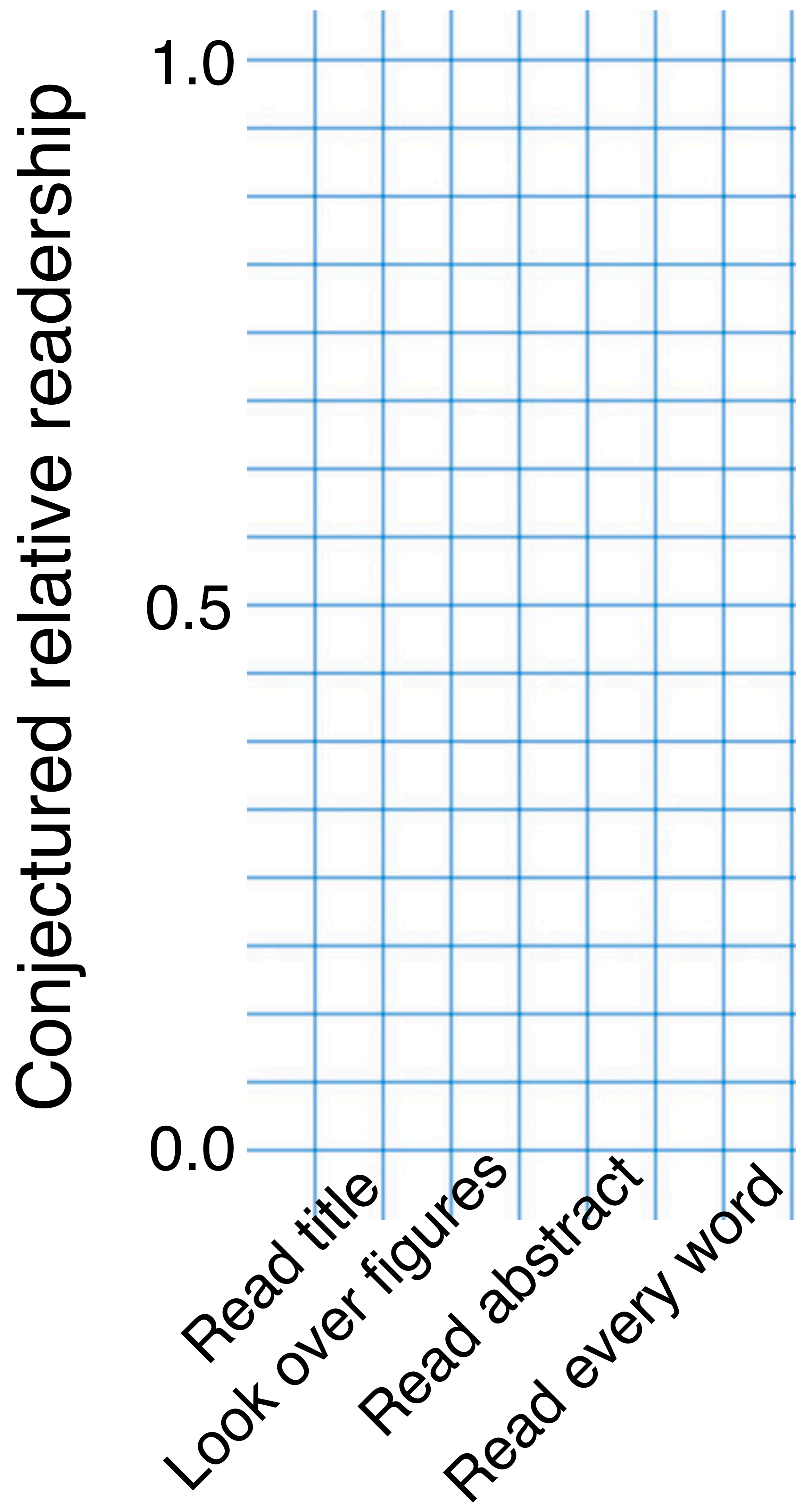
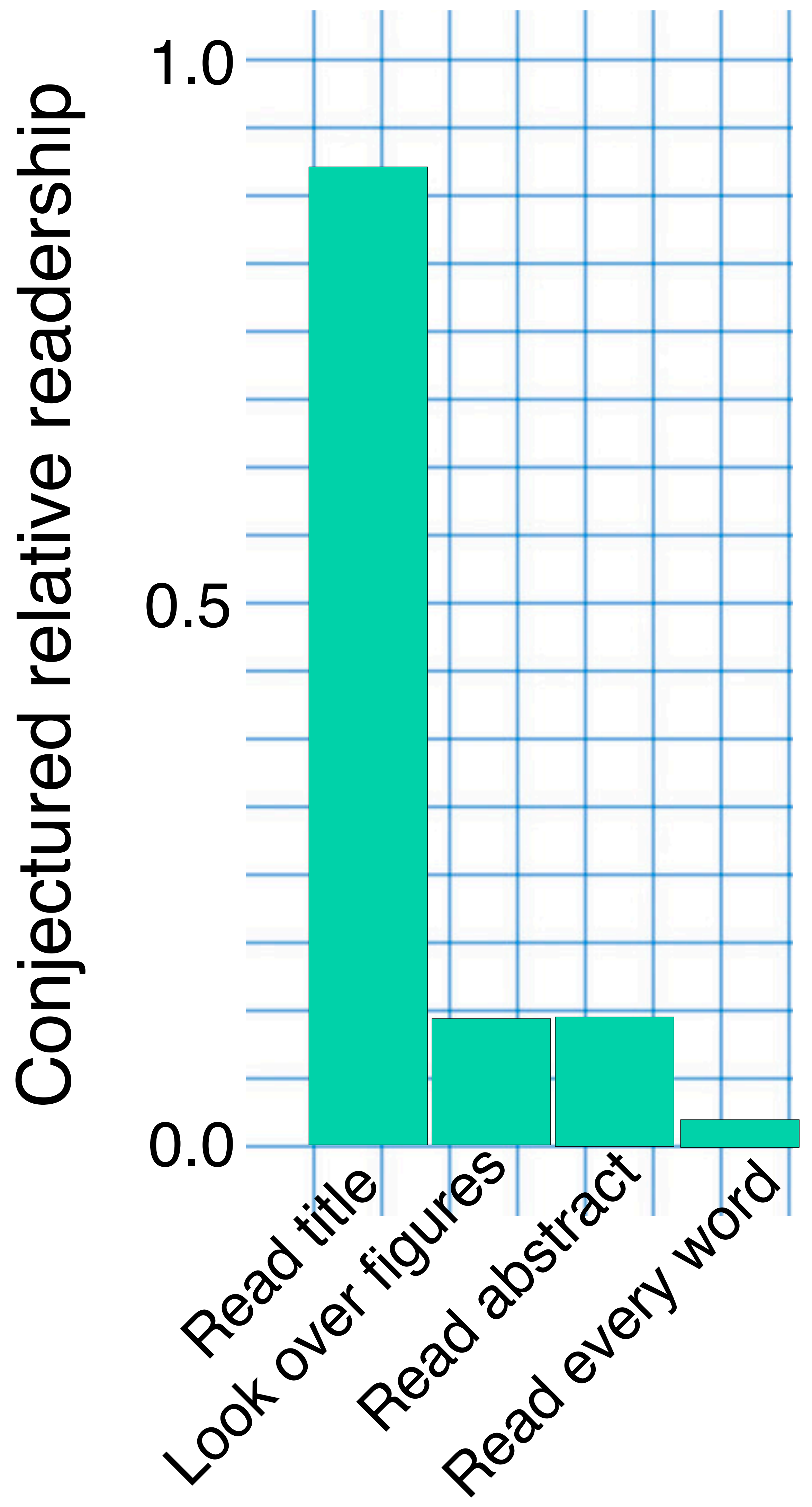
After

This editing benefits you twice: (1) you have 50% more space to tell your story, and (2) the text is easier for the reader to understand.

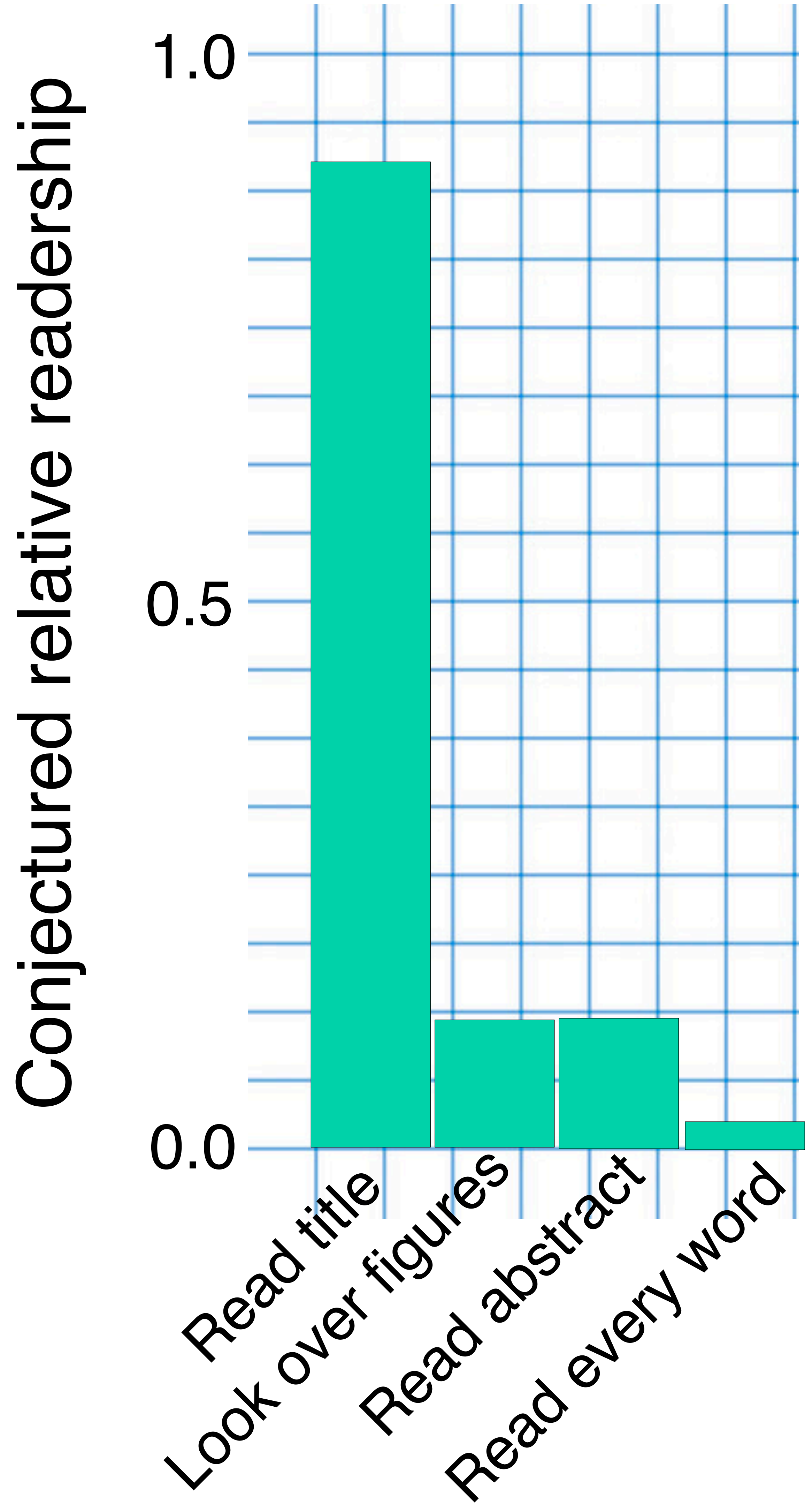
The readership of your paper



The readership of your paper



The readership of your paper



The “read every word” readers are your most important ones. But you should make the paper “work” for all the other readers, too.

Title?

IEEE TRANSACTIONS ON

INFORMATION THEORY

MARCH 1992 VOLUME 38 NUMBER 2 IETTAW (ISSN 0018-9448)

A Journal Devoted to the Theoretical and Experimental Aspects of Information Transmission, Processing and Utilization

PART II OF TWO PARTS

SPECIAL ISSUE ON WAVELET TRANSFORMS AND MULTIRESOLUTION SIGNAL ANALYSIS

I. Daubechies, S. Mallat, and A. S. Willsky — Introduction to the Special Issue 529

PAPERS

Theory and Implementation of Wavelet and Multidimensional Transforms

J. Kovačević and M. Vetterli — Nonseparable Multidimensional Perfect Reconstruction Banks and Wavelet for $\mathcal{R}n$ 533

K. Gröchenig and W. R. Madych — Multiresolution Analysis, Haar Bases, and Self-Similar Tilings of Rn 556

O. Rioul and P. Duhamel — Fast Algorithms for Discrete and Continuous Wavelet Transforms 569

E. P. Simoncelli, W. T. Freeman, E. H. Adelson and D. J. Heeger — Shiftable Multiscale Transforms 587

N. J. Munch — Noise Reduction in Tight Weyl-Heisenberg Frames 608

Time-Frequency and Event Localization

S. Mallat and W. L. Hwang — Singularity Detection and Processing with Wavelets 617

N. Delprat, B. Escudié, P. Guillemain, R. Kronland-Martinet, Ph. Tchamitchian, and B. Torrésani — Asymptotic Wavelet and Gabor Analysis: Extraction of Instantaneous Frequencies 644

B. Friedlander and B. Porat — Performance Analysis of Transient Detectors Based on a Class of Linear Data Transforms 665

R. Wilson, A. D. Calway and E. R. S. Pearson — A Generalized Wavelet Transform for Fourier Analysis: The Multiresolution Fourier Transform and Its Application to Image and Audio Signal Analysis 674

A. C. Bovik, N. Gopal, T. Emmoth, and A. Restrepo (Palacios) — Localized Measurement of Emergent Image Frequencies by Gabor Wavelets 691

Compression and Efficient Representation

R. R. Coifman and M. V. Wickerhauser — Entropy-Based Algorithms for Best Basis Selection 713

R. A. DeVore, B. Jawerth, and B. J. Lucier — Image Compression Through Wavelet Transform Coding 719

A. H. Tewfik, D. Sinha, and P. Jorgensen — On the Optimal Choice of a Wavelet for Signal Representation 747

Multiresolution Stochastic and Fractal Models

M. Basseville, A. Benveniste, K. C. Chou, S. A. Golden, R. Nikoukhah, and A. S. Willsky — Modeling and Estimation of Multiresolution Stochastic Processes 766

G. W. Wornell and A. V. Oppenheim — Wavelet-Based Representations for a Class of Self-Similar Signals with Application to Fractal Modulation 785

P. Moulin, J. A. O'Sullivan, and D. L. Snyder — A Method of Sieves for Multiresolution Spectrum Estimation and Radar Imaging 801

A. Barbé — A Level-Crossing Based Scaling-Dimensiionality Transform Applied to Stationary Gaussian Processes 814

Application to Wavelet Transforms

X. Yang, K. Wang, and S. A. Shamma — Auditory Representations of Acoustic Signals 824

D. M. Healy and J. B. Weaver — Two Applications of Wavelet Transforms in Magnetic Resonance Imaging 840

Our title

- Was:
  - Shiftable Multiscale Transforms.
- Should have been:
  - What's Wrong with Wavelets?

Our title

- Was:
  - Shiftable Multiscale Transforms.
- Should have been:
  - What's Wrong with Wavelets?

- Some classic papers with memorable titles:
  - What makes Paris look like Paris?
  - What the frog's eye tells the frog's brain.
  - An unbiased look at dataset bias.

Figures and captions

It should be easy to read the paper in a big hurry and still learn the main points. Probably most of your readers will be skimming the paper.

The figures and captions can help tell the story.

So the figure captions should be self-contained and the caption should tell the reader what to notice about the figure.

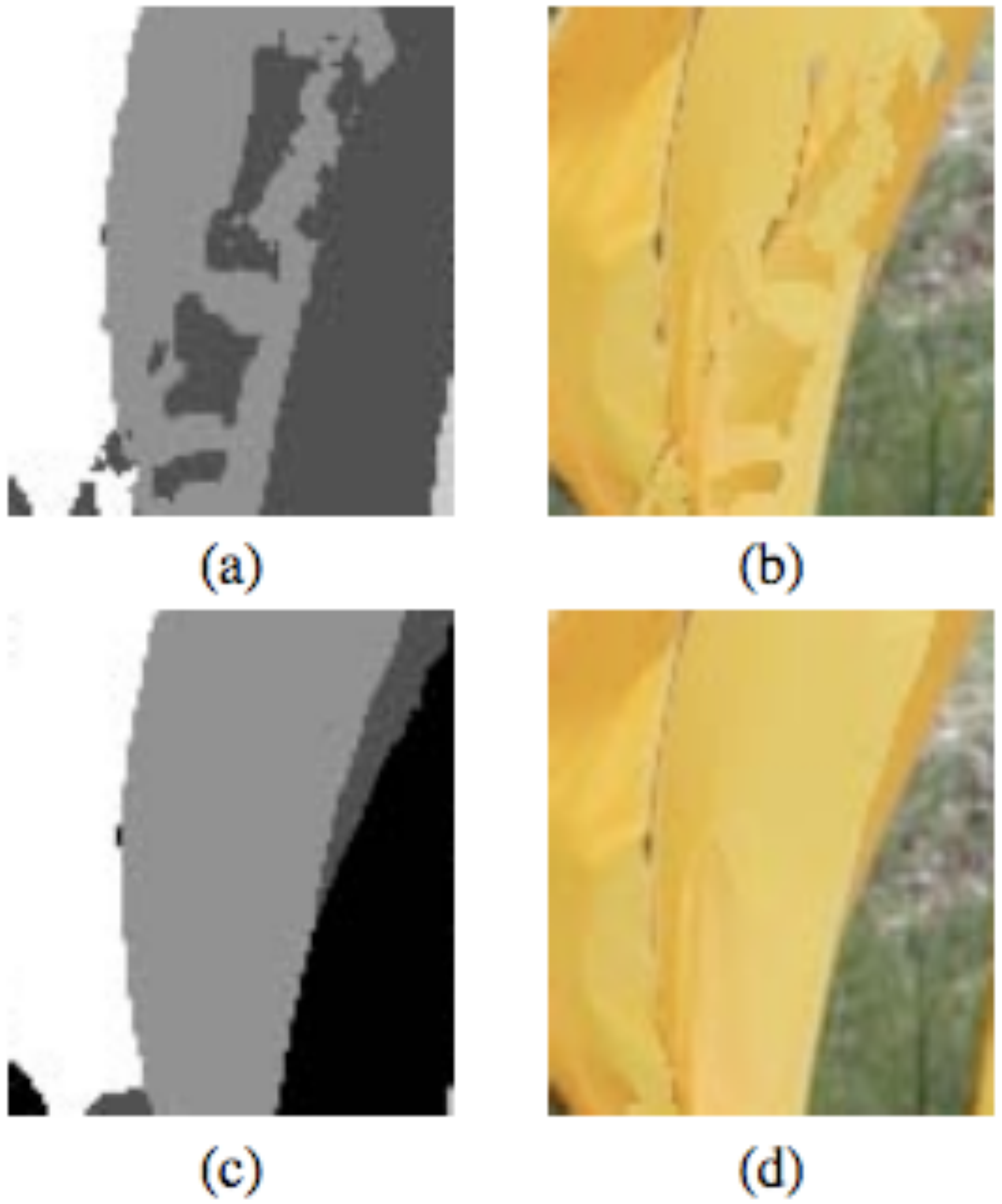


Figure 3: (a) Time-frame assignments for the front-most surface pixels, based on stereo depth measurements alone, without MRF processing. Grey level indicates the time-frame assignment at each pixel. (b) Shape-time image based on those assignments. (c) Most probable time-frame assignments, computed by MRF. (d) Resulting shape-time image. Note that the belief propagation in the MRF has removed spurious frame assignment changes.

Knuth on equations

13. Many readers will skim over formulas on their first reading of your exposition. Therefore, your sentences should flow smoothly when all but the simplest formulas are replaced by "blah" or some other grunting noise.

Mermin on equations

rule in your original manuscript.

Rule 2 (Good Samaritan rule). A Good Samaritan is compassionate and helpful to one in distress, and there is nothing more distressing than having to hunt your way back in a manuscript in search of Eq. (2.47) not because your subsequent progress requires you to inspect it in detail, but merely to find out what it is *about* so you may know the principles that go into the construction of Eq. (7.38). The Good Samaritan rule says: *When referring to an equation identify it by a phrase as well as a number.* No compassionate and helpful person would herald the arrival of Eq. (7.38) by saying "inserting (2.47) and (3.51) into (5.13) . . ." when it is possible to say "inserting the form (2.47) of the electric field **E** and the Lindhard form (3.51) of the dielectric function ϵ into the constitutive equation (5.13) . . . ."

Tone: be kind and gracious

Efros's comments within our texture synthesis paper about competing methods.

A number of papers to be published this year, all developed independently, are closely related to our work. The idea of texture transfer based on variations of [6] has been proposed by several authors [9, 1, 11] (in particular, see the elegant paper by Hertzmann et.al. [11] in these proceedings). Liang et.al. [13] propose a real-time patch-based texture synthesis method very similar to ours. The reader is urged to review these works for a more complete picture of the field.

Written from a position of security, not competition

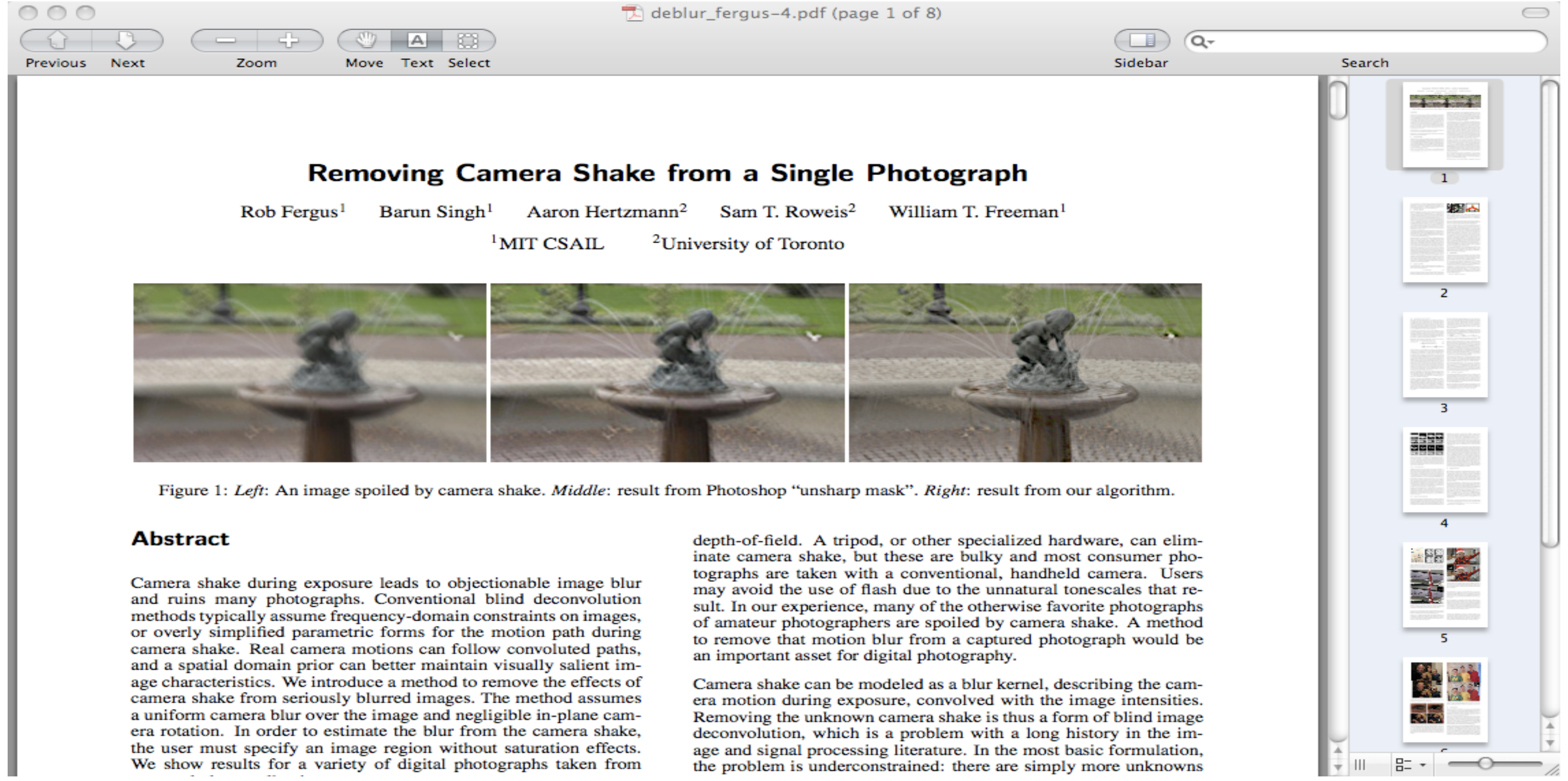
Develop a reputation for being clear and reliable

(and for doing creative, good work…)

- There are perceived pressures to over-sell, hide drawbacks, and disparage others' work. Don't succumb. (That's in both your long and short-term interests).
- "because the author was [redacted], I knew I could trust the results." [a conference chair discussing some of the reasons behind a best paper prize selection].

Be honest, scrupulously honest

Convey the right impression of performance.



deblur_fergus-4.pdf (page 1 of 8)

Removing Camera Shake from a Single Photograph

Rob Fergus[1] Barun Singh[1] Aaron Hertzmann[2] Sam T. Roweis[2] William T. Freeman[1]

[1]MIT CSAIL [2]University of Toronto

Figure 1: *Left*: An image spoiled by camera shake. *Middle*: result from Photoshop “unsharp mask”. *Right*: result from our algorithm.

Abstract

Camera shake during exposure leads to objectionable image blur and ruins many photographs. Conventional blind deconvolution methods typically assume frequency-domain constraints on images, or overly simplified parametric forms for the motion path during camera shake. Real camera motions can follow convoluted paths, and a spatial domain prior can better maintain visually salient image characteristics. We introduce a method to remove the effects of camera shake from seriously blurred images. The method assumes a uniform camera blur over the image and negligible in-plane camera rotation. In order to estimate the blur from the camera shake, the user must specify an image region without saturation effects. We show results for a variety of digital photographs taken from

depth-of-field. A tripod, or other specialized hardware, can eliminate camera shake, but these are bulky and most consumer photographs are taken with a conventional, handheld camera. Users may avoid the use of flash due to the unnatural tonescales that result. In our experience, many of the otherwise favorite photographs of amateur photographers are spoiled by camera shake. A method to remove that motion blur from a captured photograph would be an important asset for digital photography.

Camera shake can be modeled as a blur kernel, describing the camera motion during exposure, convolved with the image intensities. Removing the unknown camera shake is thus a form of blind image deconvolution, which is a problem with a long history in the image and signal processing literature. In the most basic formulation, the problem is underconstrained: there are simply more unknowns

MAP estimation of deblurring. We didn’t know why it didn’t work, but we reported that it didn’t work. Now we think we know why. Others have gone through contortions to show why they worked.

Another example: Comparison of graph cuts with belief propagation for stereo, using identical MRF parameters

Author list

- My rule of thumb: All that matters is how good the paper is. If more authors make the paper better, add more authors. If someone feels they should be an author, and you trust them and you're on the fence, add them
- It's much better to be one of many authors on a great paper than to be one of just a few authors on a mediocre paper.
- The benefit of a paper to you is a very non-linear function of its quality:
  - A mediocre paper is worth nothing.
  - Only really good papers are worth anything.

From an area chair’s point of view, the two types of borderline papers...

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http://www.amazon.com/Fun-World-Costumes-Cockroach-Costume/dp/B0038ZQYRC

- The Cockroach

You try, but you can't find a way to kill this paper. While there's nothing too exciting about it, it's pretty well written, the reviews are ok, the results show an incremental improvement. Yet another kind of boring CVPR paper. Probably 2/3 of these papers get accepted as posters, and 1/3 get rejected.

From an area chair's point of view, the two types of borderline papers...

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- The Cockroach
- The Puppy with 6 toes

http://www.imgion.com/white-cute-puppy/

A delightful paper, but with some easy-to-point-to flaw. This flaw may not be important (like 6 toes on a puppy), but makes it easy to reject the paper, even though it's so fresh and wonderful. Maybe 2/3 of these get rejected (sadly), and 1/3 get in as posters. If you have a rejected puppy, address the flaws, resubmit next time, and then perhaps it will be accepted and selected for an oral presentation.

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Quick and easy reasons to reject a paper

With the task of rejecting 75-80% of the submissions, area chairs are groping for reasons to reject a paper. Here’s a summary of reasons that are commonly used:

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- Are there mistakes or incorrect statements?

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- Are the results believable (too different than previous work)?
- Is the paper poorly written?
- Are there mistakes or incorrect statements?

Don't give them any of these easy reasons to reject your paper!

Sources on writing technical papers

- How to Get Your SIGGRAPH Paper Rejected, Jim Kajiya, SIGGRAPH 1993 Papers Chair, https://www.siggraph.org/sites/default/files/kajiya.pdf
- Ted Adelson's Informal guidelines for writing a paper, 1991. http://www.ai.mit.edu/courses/6.899/papers/ted.htm
- Notes on technical writing, Don Knuth, 1989.

http://www.ai.mit.edu/courses/6.899/papers/knuthAll.pdf

- What's wrong with these equations, David Mermin, Physics Today, Oct., 1989. http://www.ai.mit.edu/courses/6.899/papers/mermin.pdf
- Notes on writing by Fredo Durand, people.csail.mit.edu/fredo/PUBLI/writing.pdf and Aaron Hertzmann, http://www.dgp.toronto.edu/~hertzman/advice/writing-technical-papers.pdf
- Three sins of authors in computer science and math, Jonathan Shewchuck, http://www.cs.cmu.edu/~jrs/sins.html
- Ten Simple Rules for Mathematical Writing, Dimitri P. Bertsekas http://www.mit.edu:8001/people/dimitrib/Ten_Rules.html

Outline

- writing technical papers
- giving technical talks

How to give talks

- Giving good talks is important for a researcher.
- You might think, "the work itself is what really counts. Giving the talk is secondary".
- But the ability to give a good talk is like having a big serve in tennis—by itself, it doesn't win the game for you. But it sure helps. And the very best tennis players all have great serves.
- Researchers as little corporations (see http://people.csail.mit.edu/billf/publications/How_To_Do_Research.pdf).

http://imagesource.allposters.com/images/pic/SSPOD/superstock_294-341c_b~Tennis-Serve-Posters.jpg

High order bit: prepare

- Practice by yourself.
- Give practice versions to your friends.
- Think through your talk.
- You can write out verbatim what you want to say in the difficult parts.
- Ahead of time, visit where you'll be giving the talk and identify any issues that may come up.
- Preparation is a great cure for nervousness.

David Jacob's bad news

The more you work on a talk, the better it gets: if you work on it for 3 hours, the talk you give will be better than if you had only worked on it for 2 hours. If you work on it for 5 hours, it will be better still. 7 hours, better yet…

(told to me (Bill) by David on a beach in Greece, a few hours before my oral presentation at ICCV. That motivated me to leave the beach and go back to my room to work more on my talk, which paid off).

A tip to not be nervous that I found useful

- Get over it. They’re not there to see you, they’re there to hear the information. Just convey the information to them.

The different kinds of talks you'll have to give as a researcher

- 2-5 minute talks
- Longer talks (10 -20 minute conference presentations, or 30-60 minute colloquia)

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Recommendation

- For your five-minute talks, write down:
  - what problem did you address?
  - why is it interesting?
  - why is it hard?
  - what was the key to your approach?
  - how well did it work?

The (abridged) Heilmeier Catechism

George H. Heilmeier, former DARPA director (1975-1977)

- Problem definition: What are you trying to do?
- How is it done today, and what are the limits of current practice?
- What is your approach and why is it better?
- Who cares? If you are successful, what difference will it make?
- What are the mid-term and final “exams” to check for success?

The different kinds of talks you’ll have to give as a researcher

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- Longer talks (10 -20 minute conference presentations, or 30-60 minute colloquia)

Figure out how one part follows from another

Ahead of time, think through how each part motivates the next, and point that out during the talk. If one part doesn't motivate the next, consider re-ordering the talk until it has that feel.

Your audience

Your audience

- Your image of your audience:

Your audience

- Your image of your audience:
  - Paying attention, listening to every word

Your audience

- Your image of your audience:
  - Paying attention, listening to every word

Your audience

- Your image of your audience:
  - Paying attention, listening to every word

- Your audience in reality:

Your audience

- Your image of your audience:
  - Paying attention, listening to every word
- Your audience in reality:
  - Tired, hungry, not wanting to sit through yet another talk at the conference…

http://tbn0.google.com/images?
q=tbn:4oWYOjaSp4vopM:http://
bakery.grillsforallseasons.com/photos/wedding_cake3.jpg

<u>Layering the talk</u>. When we read a paper, headings and sections help us follow the paper. You should provide the verbal equivalents of headings to the listener.

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The probability of an observation has three terms to it.

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So now, with these tools in hand, we can apply this methods to real images. blah blah blah blah blah blah blah blah blah blah blah blah blah blah blah blah blah blah

You tell the story at several different levels of detail

The main idea

Then dive into lots of details describing what you've done,

Then come up for air, summarize, and say what this leads to next,

Then more details or equations fleshing that next part out,

Ways to engage the audience

- So you’ve been talking on and on. You want to break things up and keep the audience engaged. Can you think of a way to bring the audience into the talk?
- Demos can also help.
- Or add audience participation components to the talk. For human or computer vision talks, you can often present to the audience what the task is that the human or computer has to solve.
- The audience loves to figures things out, to solve puzzles, to make guesses. Feed those desires.

Two ways to present a solution to a problem

The direct, “here is the problem, and here is the solution”, way. This is the *right* way if you are under time constraints, like for a paper presentation at a conference.

The indirect way: “manipulating” your audience into thinking you’re an idiot.

The “direct” way of presenting a method

“Here is the problem, and here is the solution”.

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Vincent's "You got to trick your audience" way

- Key idea: "manipulating" your audience into thinking you're an idiot, to then surprise them with evidence to the contrary.
  - Introduce the problem. Introduce it in *great detail* - really make sure they understand the problem. *They will start thinking about the way you are going to solve the problem in a bit.*
  - Then, start talking about the *obvious* solution. *This will be the solution they came up with*. Don't do this fast - spend some time on it. *Everyone will think you're an idiot: You've done the obvious thing, duh!*
  - Now, pull the rug: Tell them why that solution is *stupid, and tell them exactly how and why it is stupid and will not work.*
  - **Then** tell them the actual solution! You will have their undivided attention, and they won't forget it ;)

Ted Adelson

Ted Adelson

- “people like to see a good fight”

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- The flat earth theory predicts that ships will appear on the horizon as small versions of the complete ship. Under that theory, you’d expect approaching ships to look like this:

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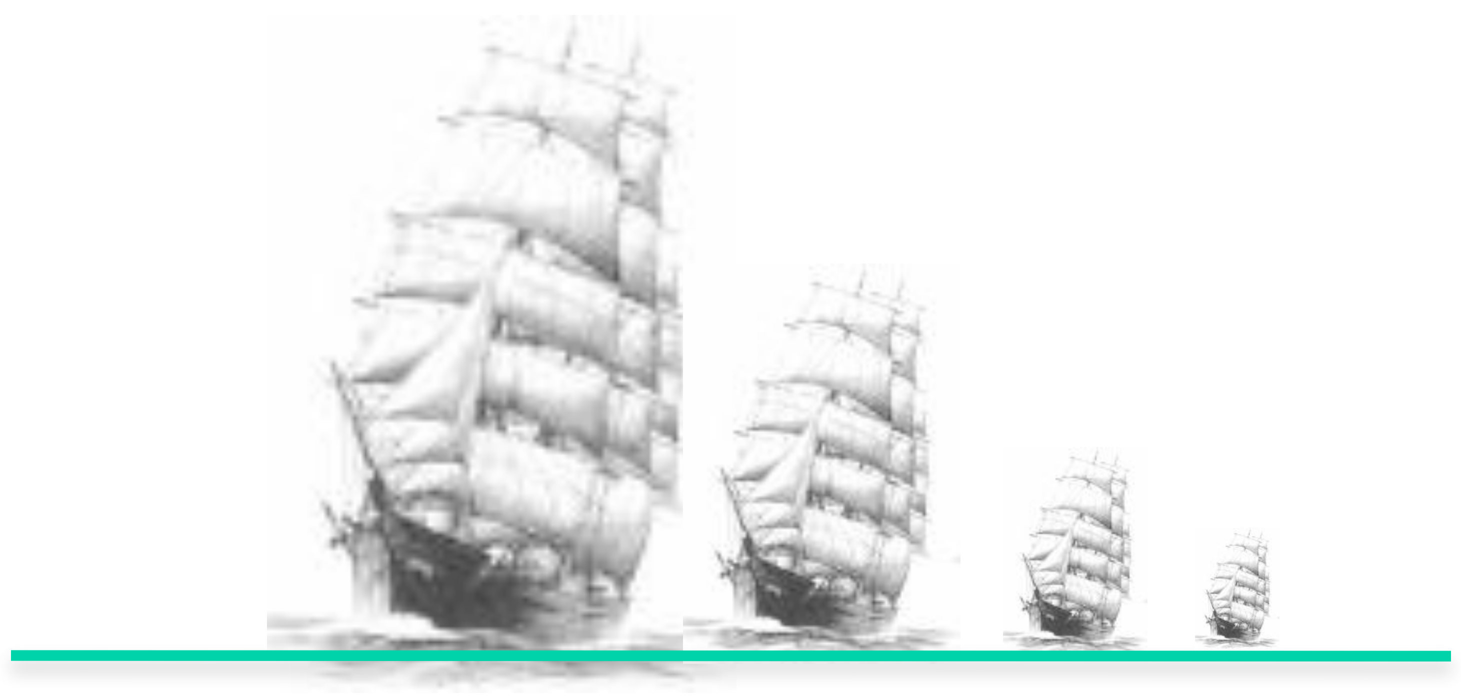


Present a fight

Whereas the round earth theory predicts that the top of the sails will appear first, then gradually the rest of the ship below it.

Then reveal the evidence that resolves the fight…

Then reveal the evidence that resolves the fight…

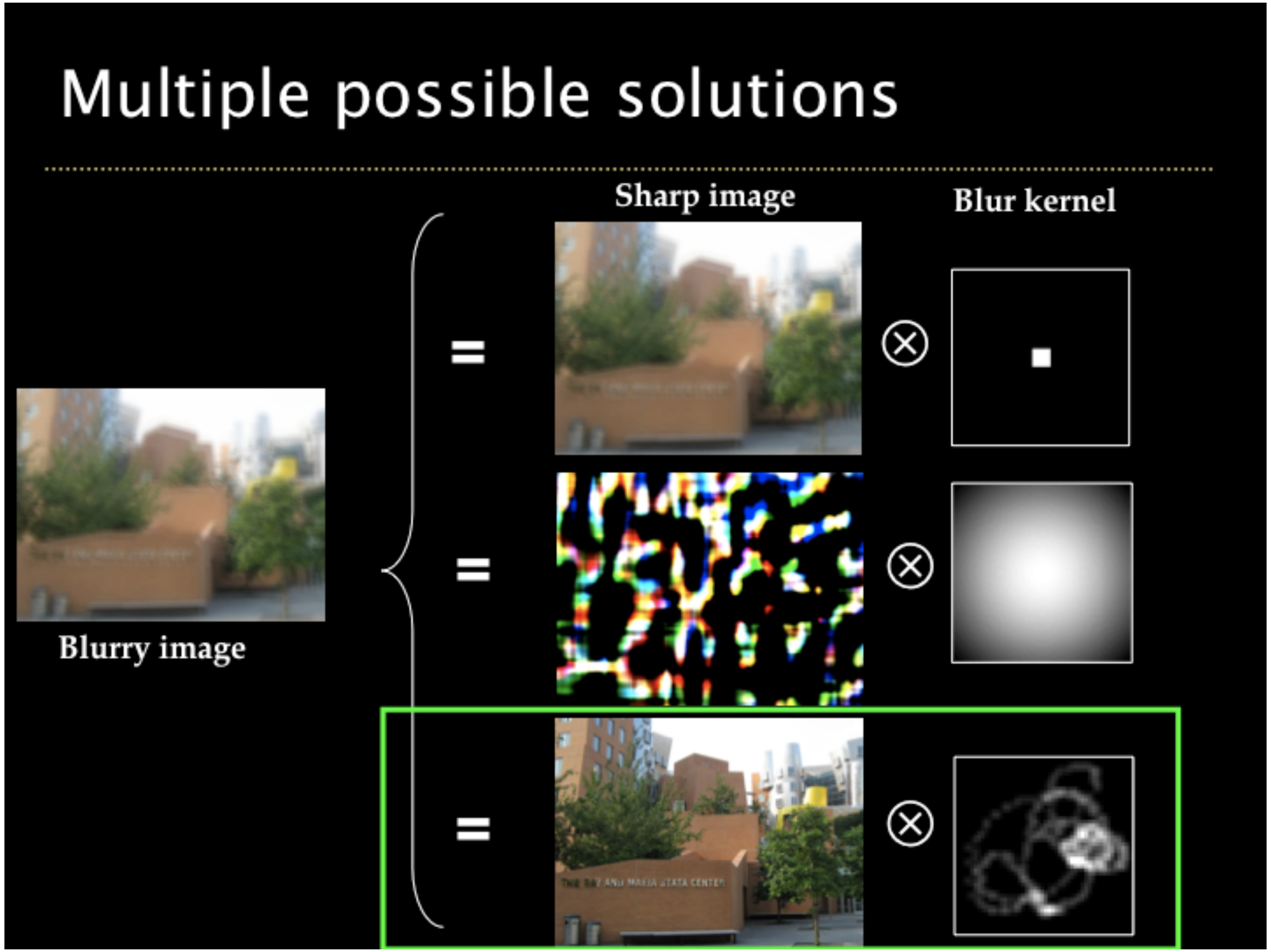
http://www.flickr.com/photos/mnsomero/
2738807250/

Add dynamics to the talk

http://www.nch.ie/dynamic/img/Mariss%20Jansons%20%20new.jpg

- A talk is a story. As in a story, there can be different levels of excitement or tension in different parts of the talk. This makes it easier for the audience to pay attention to what you're saying. Perhaps move to another location.
- I like to find some part of the work that really grabs me, that I'm really excited about, and let that show through. (The audience loves to see you be excited. Not all the time, but when appropriate).

"I love this problem; it's beautifully underdetermined. There are lots of different ways we can explain the observed blurry image. It could be that that's what was there in the world, and we took a sharp picture of it…."



What I think the audience of a technical talk wants

To have everything follow and make sense.

To learn something, to develop their intuition.

To connect with the speaker, to share their excitement.

They want to watch you love something!

Alan Alda: https://www.youtube.com/watch?v=j4XgjkXDxss, and others

Let the audience see your personality

- They want to see you enjoy yourself.
- They want to see what you love about the work.
- People really respond to the human parts of a talk. Those parts help the audience with their difficult task of listening to an hour-long talk on a technical subject. What was easy, what was fun, what was hard about the work?
- Don’t be afraid to be yourself and to be quirky.

http://is3.okcupid.com/users/112/250/11225140098321842389/mt1112532356.jpg

How to end a talk

- People often say “are there any questions?” but then people don’t know whether to applaud or to raise their hand.
- If you say “thank you”, then everyone knows that they’re supposed to applaud now. After that is over, then you can ask for questions.