

Dynamic visualization of high-dimensional data via low-dimension projections and sectioning across 2D and 3D display devices

A thesis submitted for the degree of

Doctor of Philosophy

by

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Acknowledgements

I would like to thank ...

Declaration

I hereby declare that this thesis contains no material which has been accepted for the award of any other degree or diploma in any university or equivalent institution, and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

Nicholas S Spyrison

Preface

The material in Chapter 1 has been submitted to *Something interesting jornal* for possible publication.

The contribution in Chapter 3 of this thesis was presented in the super awesome conference held in Dublin, Ireland, in July 2015.

Abstract

This thesis is about ...

Chapter 1

Introduction

This is where you introduce the main ideas of your thesis, and an overview of the context and background.

In a PhD, Chapter 2 would normally contain a literature review. Typically, Chapters 3–5 would contain your own contributions. Think of each of these as potential papers to be submitted to journals. Finally, Chapter 6 provides some concluding remarks, discussion, ideas for future research, and so on. Appendixes can contain additional material that don't fit into any chapters, but that you want to put on record. For example, additional tables, output, etc.

Chapter 2

Literature review

2.1 Touring

2.1.1 Overview

In univariate data sets histograms, or smoothed density curves are employed to visualize data. In bivariate data scatterplots and contour plots (2-d density) can be employed. In three dimensions the two most common techniques are: 2-d scatter plot with the 3rd variable as an aesthetic (such as, color, size, height, *etc.*) or rendering the data in a 3-d volume using some perceptive cues giving information describing the seeming depth of the image ¹. When there are 4 variables: 3 variables as spatial-dimensions and a 4th as aesthetic, or a scatterplot matrix consisting of 4 histograms, and 6 unique combinations of bivariate scatterplots.

Let p be the number of numeric variables; how do we visualize data for even modest values of p (say 6 or 12)? It's far too common that visualizing in data-space is dropped altogether in favor of modeling parameter-space, model-space, or worse: long tables of statistics without visuals (Wickham, Cook, and Hofmann, 2015). Yet, we all know of the risks inherent in relying too heavily on parameters alone (Anscombe, 1973; Matejka and Fitzmaurice, 2017). So why do we move away from visualizing in data-space? Scalability,

¹Graphs of data depicting 3 dimension are typically printed on paper, or rendered on a 2-d monitor, they are intrinsically 2-d images. They are sometimes referred to as 2.5-d, or more frequently erroneously referred to as 3-d, more on this later.

in a word, we are not familiar with methods that allow us to concisely depict and digest $p \geq 5$ or so dimensions. This is where dimensionality reduction comes in. Specifically, we will be focusing on a specific group called touring. In the interest of time I will not belabor the diversity of dimensionality reduction, (see [Grinstein, Trutschl, and Cvek (2002); Carreira-Perpinán (1997); heer_tour_2010] for a quick summary). Suffice it to say that touring has a couple of salient features: linear transformations such that we can interpolate back to the original variable space and does not discard dimensions, something that is common to other linear techniques. By employing the breadth of tours we are able to preserve the visualization of data-space, and with it, the intrinsic understanding of structure and distribution of data that is more succinct or beyond the reach of statistic values alone.

Touring is a linear dimensionality reduction technique that orthogonally projects p -space down to $d(\leq p)$ dimensions. Many such projections are interpolated, each making local rotations in p -space. These frames are then viewed in order to the effect of watching an animation of the lower dimensional embedding changing as p -space is manipulated. Shadow puppets offer a useful analogy to aid in conceptualizing touring. Imagine a fixed light source facing a wall. When a hand or puppet is introduced the 3-dimensional object projects a 2-dimensional shadow onto the wall. This is a physical representation of a simple projection, that from $p = 3$ down to $d = 2$. If the object rotates then the shadow correspondingly changes. Observers watching only the shadow are functionally watching a 2-dimensional tour as the 3-dimensional object is manipulated.

Terminology

n, p (sometimes called d by Wegman, or n), d (sometimes called k by wegman, or d in tourr)

2.1.2 History

Touring was first introduced by Asimov in 1985 with his purposed Grand Tour(Asimov, 1985) at Stanford University. In which, Asimov suggested three types of Grand Tours:

torus, at-random, and random-walk. The specifics of which will be discussed below in the Typology section.

TALK ABOUT maths Here::

Note that the the above methods have no input from the user aside from the starting basis. The bulk of touring development since has largely been around dynamic display, user interaction, geometric representation, and application.

This works well when the number of dimensions being toured is small (in the neighborhood of 5-10), yet the number of view, or 2-frames and we can produce from p -space suffers from the so called blessing/curse of dimensionality. In which the plethora of degrees of freedom either offer many (non-unique) solutions to a problem or something that becomes ever increasing unlikely,

2.1.3 Tour path

A fundamental aspect of touring is the path of rotation. Of which there are four primary distinctions(Buja et al., 2005): random choice, precomputed choice, data driven, and manual control.

- *grand tour*, a constrained random choice p -space. Paths are constrained for changes in direction small enough to maintain continuity and aid in user comprehension
 - torus-surface (Asimov, 1985)
 - Geodesic
 - at-random
 - random-walk
 - *local tour*, a sort of grand tour on leash, such that it goes to a nearby random projection before returning to the original position and iterating
- *guided tour*, data driven tour optimizing some objective function via (stochastic) gradient descent (Hurley and Buja, 1990).
 - holes (Cook, Buja, and Cabrera, 1993) - iterates projections that add more white space to the center of the projection.

- *cmass* (Cook, Buja, and Cabrera, 1993) - find the projection with the most density or mass in the center.
 - *lda* (Lee et al., 2005) - linear discriminant analysis, seeks a projection where 2 or more classes are most separated.
 - *pda* - principal component analysis finding where the data is most spread (1d only).
 - other user-defined objective function (Wickham et al., 2011).
- *planned tour*, Precomputed choice, In which the path has already been generated or defined.
 - *little tour* (McDonald, 1982), where every permutation of variables is stepped through in order, analogous to a brute-force or exhaustive search.
 - a saved path of any other tour
 - *manual tour* - Manual control, a constrained rotation on selected manipulation variable and magnitude (Cook and Buja, 1997). Typically used to explore the local area after identifying an interesting feature from another tour.
 - *dependance tour*, combination of n independent 1d tours. A vector describes the axis each variable will be displayed on. ie $c(1, 1, 2, 2)$ is a 4 to 2d tour with the first 2 variables on on the first axis, and the remaining on the second.
 - *correlation tour* (Buja, Hurley, and McDonald, 1987), a special case of the dependence tour, analogous to canonical correlation analysis

2.1.4 Geometrics and display dimension

Up to this point we have been talking about 2d scatterplots, which offer the first and a simple case for viewing lower-dimensional embeddings of p -space. However, other geometrics (or geoms) offer perfectly valid orthonormal projections as well.

- 1d geoms

- 1-d densities: such as histogram, average shifted histograms([scott85](#)), and kernel density([scott95](#)).
- image: ([Wegman](#))
- time series: where multivariate values are independently lagged to view peak and trough alignment. Currently no package implementation, but use case is discussed in (Cook and Buja, [1997](#)).
- 2d geoms
 - 2-d density ([NS](#))
 - scatterplot
 -
- 2.5d, 3d geoms {ADD FOOTNOTE ABOUT 2.5d vs 3d}
 - Anaglyphs, sometimes called stereo, where (typically) red images are positioned for the left channel and cyan for the right, when viewed with corresponding filter glasses give the depth perception of the image.
 - Depth, which use some subset of depth cues, most commonly size and/or color of data points.
- d -dim geoms
 - Andrews curves ([Andrews, 1972](#)), smoothed variant of parallel coordinate plots, discussed below.
 - Chernoff faces ([Chernoff, 1973](#)), variables linked to size of facial features for rapid cursory like-ness comparison of observations.
 - Parallel coordinate plots ([Ocagne, 1885](#)), where any number of variables are plotted in parallel with observations linked to their corresponding variable value by polylines.
 - Scatterplot matrix ([Becker and Cleveland, 1987](#)), showing a triangle matrix of bivariate scatterplots with 1-d density on the diagonal.
 - Radial glyphs, radial variants of parallel coordinates including radar, spider, and star glyphs ([Siegel et al., 1972](#)).

2.1.5 Application

Below is a non-exhaustive list of software implementing touring in some degree, ordered by descending year:

- Spinifex (**spinifex**) – for Linux, Unix, and Windows.
- Tourr (Wickham et al., [2011](#)) – for Linux, Unix, and Windows. R package.
- CystalVision (Wegman, [2003](#)) – for Windows.
- GGobi (Swayne et al., [2003](#)) – for Linux and Windows.
- DAVIS (Huh and Song, [2002](#)) – Java based, with GUI.
- VRGobi (Nelson, Cook, and Cruz-Neira, [1998](#)) – for use with the C2 in stereoscopic 3d displays.
- ExplorN (Carr, Wegman, and Luo, [1996](#)) – for SGI Unix.
- XGobi (Swayne, Cook, and Buja, [1991](#)) – for Linux, Unix, and Windows (via emulation).
- XLispStat (Tierney, [1990](#)) – for Unix, and Windows.
- Prim-9 (Asimov, [1985](#); Fisherkeller, Friedman, and Tukey, [1974](#)) – on an internal operating system.

Support and maintenance of such implementations give them a particularly short life span, while conceptual abstraction and technically heavier implementations have hampered user growth. There have been notable efforts to diminish the barriers to entry and make touring more approachable as a data exploration tool [Huh and Song ([2002](#)); Swayne et al. ([2003](#)); Wegman ([2003](#)); Wickham et al. ([2011](#)); huang_tourrgui:_2012].

2.2 Virtual reality

Chapter 3

***spinifex*: An R package that provides manual rotations in high-dimensions**

3.1 Abstract

The tour algorithm, and its various versions provide a systematic approach to viewing low-dimensional projections of high-dimensional data. It is particularly useful for understanding multivariate data, and useful in association with techniques for dimension reduction, supervised and unsupervised classification. The R package *tourr* provides many methods for conducting tours on multivariate data. This paper discusses an extension package which adds support for the manual tour, called *spinifex*. It is particularly useful for exploring the sensitivity of structure discovered in a projection by a guided tour, to the contribution of a variable. *Spinifex* utilizes the animation packages *plotly* and *gganimation* to allow users to rotate a variable into and out of a chosen projection.

Keywords: grand tour, projection pursuit, manual tour, high dimensional data, multivariate data, data visualization, statistical graphics, data science, data mining.

3.2 Introduction

The manual tour was described in Cook and Buja (1997), and allows a user to rotate a variable into and out of a 2D projection of high-dimensional space. The primary purpose is to determine the sensitivity of structure visible in a projection to the contributions of a variable. Manual touring can also be useful for exploring the local structure once a feature of interest has been identified, for example, by a guided tour (Cook et al., 1995). The algorithm for a manual tour allows rotations in horizontal, vertical, oblique, angular and radial directions. Rotation in a radial direction, would pull a variable into and out of the projection, which allows for examining the sensitivity of structure in the projection to the contribution of this variable. This type of manual rotation is the focus of this paper.

A manual tour relies on user input, and thus has been difficult to program in R. Ideally, the mouse movements of the user are captured, and passed to the computations, driving the rotation interactively. However, this type of interactivity is not simple in R. This has been the reason that the algorithm was not incorporated into the *tourr* package. *Spinifex* utilizes two new packages for conducting animations, *plotly* (Sievert, 2018) and *gganimate* (Pedersen and Robinson, 2019), to conduct a manual tour. From a given projection, the user can choose which variable to control, and the animation sequence is generated to remove the variable from the projection, and then extend its contribution to be the sole variable in one direction. This allows the viewer to assess the change in structure induced in the projection by the variable contribution.

The paper is organized as follows. Section 3.3 explains the algorithm using a toy dataset. Section 3.5 illustrates how this can be used for sensitivity analysis. The last section summarizes the work and discusses future research.

3.3 Algorithm

Creating a manual tour animation requires these steps:

1. Provided with a 2D projection, choose a variable to explore. This is called the “manip” variable.

2. Create a 3D manipulation space, where the *manip* variable has full contribution.
3. Generate a rotation sequence which zero's the norm of the coefficient and also increases it to 1.

These steps are described in more detail below.

3.3.1 Notation

This section describes the notation used in the algorithm description. The data to be displayed is an $n \times p$ numeric matrix.

$$\mathbf{X}_{n \times p} = \begin{bmatrix} X_{1,1} & \dots & X_{1,p} \\ X_{2,1} & \dots & X_{2,p} \\ \vdots & \ddots & \vdots \\ X_{n,1} & \dots & X_{n,p} \end{bmatrix}$$

and an orthonormal d -dimensional projection matrix is

$$\mathbf{B}_{[p,d]} = \begin{bmatrix} B_{1,1} & \dots & B_{1,d} \\ B_{2,1} & \dots & B_{2,d} \\ \vdots & \ddots & \vdots \\ B_{p,1} & \dots & B_{p,d} \end{bmatrix}$$

The algorithm is primarily operating on the projection basis and utilizes the data only when making a display.

3.3.2 Toy data set

The flea data from the R package *tourr* (Wickham et al., 2011), is used to illustrate the algorithm. The data, originally from Lubischew (1962), contains 74 observations across 6

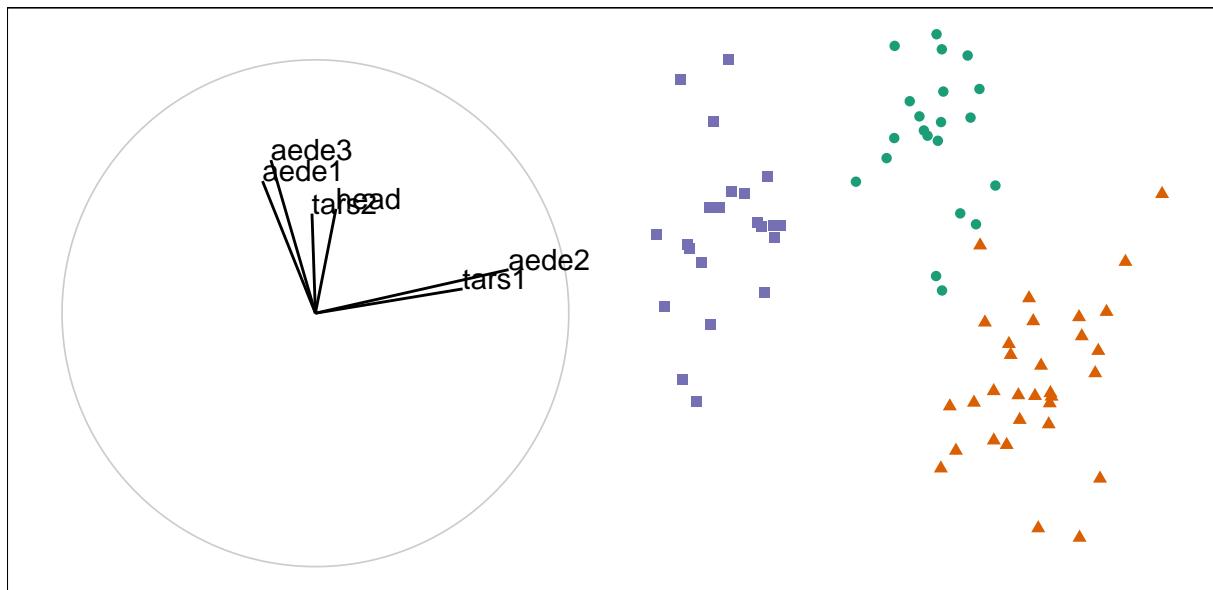


Figure 3.1: *Basis reference frame (left) and projected data (right) of standardized flea data. Basis identified by holes-index guided tour. The variables `aede2` and `tars1` contribute mostly in the x direction, whereas the other variables contribute mostly in the y direction. We'll select `aede2` as our manipulation variable to see how the structure of the projection changes as we rotate `aede2` into and out of the projection.*

variables, which physical measurements of the insects. Each individual belonged to one of three species.

A guided tour on the flea data is conducted by optimizing on the `holes` index (Cook, Swayne, and Buja, 2007). In a guided tour the data the projection sequence is shown by optimizing an index of interest. The holes index is maximized by when the projected data has a lack of observations in the center. Figure 3.1, shows an optimal projection of this data. The left plot displays the projection basis, while the right plot shows the projected data. The display of the basis has a unit circle with lines showing the horizontal and vertical contributions of each variable in the projection. Here is is primarily `tars1` and `aede2` contrasting the other four variables. In the projected data it can be seen that there are three clusters, which have been colored, although not used in the optimization. The question that will be explored in the explanation of the algorithm is how important is `aede2` to the separation of the clusters.

The left frame of 3.1 shows the reference frame for the basis. It describes the X and Y contributions of the basis as it projects from the 6 variable dimensions down to 2. Call `view_basis()` on a basis to produce a similar image as a `ggplot2` object. The right side shows how the data looks projected through this basis. You can project a single basis at any time through the matrix multiplication $\mathbf{X}_{[n, p]} * \mathbf{B}_{[p, d]} = \mathbf{P}_{d[n, d]}$ to such effect.

3.3.3 Step 1 Choose variable of interest

Select a manipulation variable, k . Initialize a zero vector e , and set the k -th element set to 1.

$$\mathbf{e}_{k [p, 1]} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix}_{[p, 1]}$$

In figure 3.1, above, notice that the variables `tars1` and `aede2` are almost orthogonal to the other 4 variables and control almost all of the variation in the x axis of the projection. `Aede2` has a larger contribution in this basis, so we'll select it

3.3.4 Step 2 Create the manip space

Use the Gram-Schmidt process to orthonormalize the concatenation of the basis and e yielding the manipulation space.

$$\mathbf{M}_{[p, d+1]} = \text{Orthonormalize}_{GS}(\mathbf{B}_{[p, d]} | \mathbf{e}_{k [p, 1]})$$

$$= \text{Orthonormalize}_{GS} \left(\left[\begin{array}{ccc|c} B_{1,1} & \dots & B_{1,d} & 0 \\ B_{2,1} & \dots & B_{2,d} & 0 \\ \vdots & \ddots & \vdots & \vdots \\ B_{k,1} & \dots & B_{k,d} & 1 \\ \vdots & \ddots & \vdots & \vdots \\ B_{p,1} & \dots & B_{p,d} & 0 \end{array} \right] \right)$$

In R it looks like the below chunk. `tourr::orthonormalise()` uses the Gram Schmidt process (rather than Householder reflection) to orthonormalize.

```
e          <- rep(0, len = nrow(basis))
e[manip_var] <- 1
manip_space <- tourr::orthonormalise(cbind(basis, e))
```

Adding an extra dimension to our basis plane allows for the manipulation of the specified variable while the others are kept fully within the basis plane. orthonormalizing rescales the matrix without bringing the other variables into this new axis. An illustration of such can be seen below in 3.2.

Imagine being able to grab hold of the red axis and rotate it changing the projection onto the basis plane. This is what happens in a manual tour. By controlling the angle between the axis and the basis plane we change the contribution of the manipulation variable on the projection.

3.3.5 Step 3 Generate rotation

Define a set of values for ϕ_i , the angle of out-of plane rotation, orthogonal to the projection plane. This corresponds to the angle between the red axis and the blue plane in 3.2.

For i in 1 to n_slides :

For each ϕ_i , post multiply the manipulation space by a rotation matrix, producing as many basis-projections.

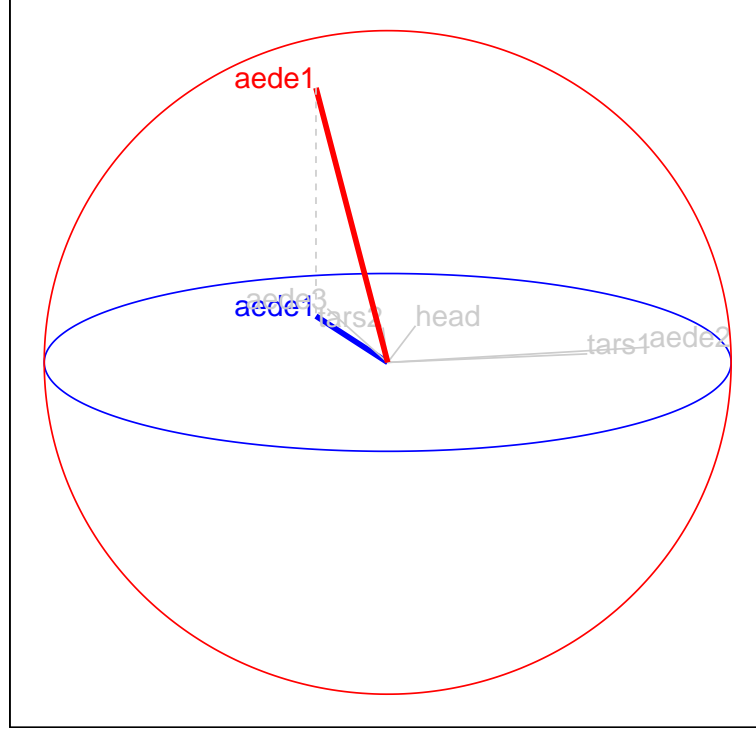


Figure 3.2: Manipulation space for controlling the contribution of aede2 of standardized flea data. Basis was identified by holes-index guided tour. The out of plane axis, in red, shows how the manipulation variable can be rotated, while other dimensions stay embedded within the basis plane.

$$\mathbf{P}_{b[p, d+1, i]} = \mathbf{M}_{[p, d+1]} * \mathbf{R}_{[d+1, d+1]}$$

$$= \begin{bmatrix} M_{1,1} & M_{1,2} & M_{1,3} \\ M_{2,1} & M_{2,2} & M_{2,3} \\ \vdots & \vdots & \vdots \\ M_{p,1} & M_{p,2} & M_{p,3} \end{bmatrix}_{[p, d+1]} * \begin{bmatrix} c_\theta^2 c_\phi s_\theta^2 & -c_\theta s_\theta (1 - c_\phi) & -c_\theta s_\phi \\ -c_\theta s_\theta (1 - c_\phi) & s_\theta^2 c_\phi + c_\theta^2 & -s_\theta s_\phi \\ c_\theta s_\phi & s_\theta s_\phi & c_\phi \end{bmatrix}_{[3, 3]}$$

For the $d = 2$ case:

Where:

θ is the angle that lies on the projection plane (*ie.* on the XY plane)

ϕ is the angle orthogonal to the projection plane (*ie.* in the Z direction)

c_θ is the cosine of θ

c_ϕ is the cosine of ϕ

s_θ is the sine of θ

s_ϕ is the sine of ϕ

In application: compile the sequence of ϕ_i and create an array (or long table) for each rotated manipulation space. ϕ is actually the angle relative to the ϕ_1 , we find the transformation $\phi_i - \phi_1$ useful to discuss ϕ relative to the basis plane.

```
for (phi in seq(seq_start, seq_end, phi_inc_sign)) {  
  slide <- slide + 1  
  tour[, , slide] <- rotate_manip_space(manip_space, theta, phi)[, 1:2]  
}
```

3.3

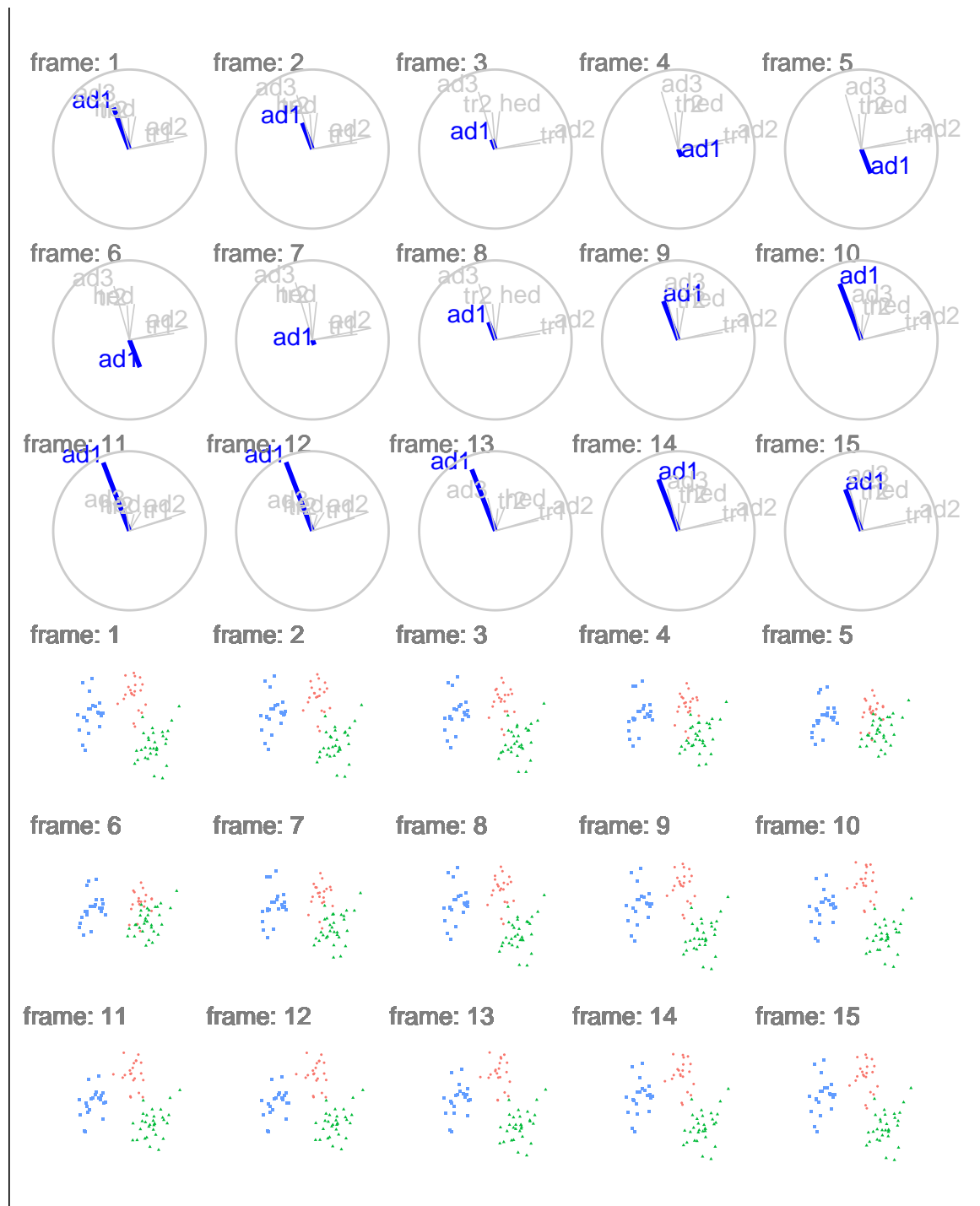


Figure 3.3: Rotated manipulation spaces, a radial manual tour manipulating *aded2* of standardized flea data. The manipulation variable, *aede2*, extends from it's initial contribution to a full contribution to the projection before decreasing to zero, and then retruning to it's inital state.

3.4 Display projection sequence

To get back to data-space pre-multiply each projection basis by the data for the projection in data-space.

$$\mathbf{P}_{d[n, d+1]} = \mathbf{X}_{[n, p]} * \mathbf{P}_{b[p, d+1]} \quad (3.1)$$

$$= \begin{bmatrix} X_{1,1} & \dots & X_{1,p} \\ X_{2,1} & \dots & X_{2,p} \\ \vdots & \vdots & \vdots \\ X_{n,1} & \dots & X_{n,p} \end{bmatrix}_{[n, p]} * \begin{bmatrix} P_{b:1,1} & P_{b:1,2} & P_{b:1,3} \\ P_{b:2,1} & P_{b:2,2} & P_{b:2,3} \\ \vdots & \vdots & \vdots \\ P_{b:p,1} & P_{b:p,2} & P_{b:p,3} \end{bmatrix}_{b[p, d+1]} \quad (3.2)$$

Plot the first 2 variables from each projection in sequence for an XY scatterplot. The remaining variable is sometimes linked to a data point aesthetic to produce depth cues used in conjunction with the XY scatterplot.

tourr utilizes R's base graphics for the display of tours. Use `render_plotly()` to display as an dynamic plotly Sievert (2018) object or `render_gganimate()` for a gganimate Pedersen and Robinson (2019) graphic. A third notable animation related package is *animation* Xie et al. (2018). It's not yet implemented in *spinifex* as it uses base graphics, whereas the former two are compatible with *ggplot2*.

Interaction with graphics in R is limited. Traditionally, all commands are passed to the R via calls to the console, conflicting with user engagement. Some recent packages have made advancement into this direction such as with the use of the R package *shiny*, which custom-made applications can be hosted either locally or remotely and interact with the R console, allowing for developers to code dynamic content interaction. To a lesser extent *plotly* offers static interactions with contained object, such as tool tips, brushing, and linking without communicating back to the R console.

Storing the each data point and all of the overhead though goes into dynamic graphics if very inefficient. In the same way that we performed math the bases, that is the same approach storage and sharing tours. Consider the manual tour, we can store the salient

features in 3 basis, where ϕ is at it's starting, minimum, and maximum values. The frames in between can be interpolated by supplying angular speed or number of desired frames. By using the `tourr::save_history()` we can do just that. Save such tour path history and a single set of the data offers a performant storage and transferring.

3.5 Application

In a recent paper, Wang et al. (2018), the authors aggregate and visualize the sensitivity of hadronic experiments. The authors introduce a new tool, PDFSense, to aid in the visualization of parton distribution functions (PDF). The parameter-space of these experiments lies in 56 dimensions, $\delta \in \mathbb{R}^{56}$, and are presented in this work in 3-d subspaces of the 10 first principal components and non-linear embeddings.

The work in Cook, Laa, and Valencia (2018) applies touring for discern finer structure of this sensitivity. Table 1 of Cook et. al. summaries the key findings of PDFSense & TFEF (tensorflow embedded projection) and those from touring. Below we identify the basis projection for figures 7 and 8 use manual tours to for finer exploration of the local structure.

3.5.1 DIS cluster

In figure 8 of Cook, Laa, and Valencia (2018), the authors look at the 6 first principal components, containing 48% of the variation held within the data when dimensions at centered, but not sphered (6 components explains 53% of sphered data, sphered data not used below). Data are colored by experiment type with 'dimuon SIDIS' in green , 'DIS HERA1+2' experiments in black, and 'charm SIDIS' in red.

```
## Warning: Removed 1 rows containing missing values (geom_path).
```

Dynamic version of this manual tour can be found at: https://nspyrison.netlify.com/thesis/discluster_manualtour_pc6/ The page take a bit to load as the .html object is large.

```
## Warning: Removed 1 rows containing missing values (geom_path).
```

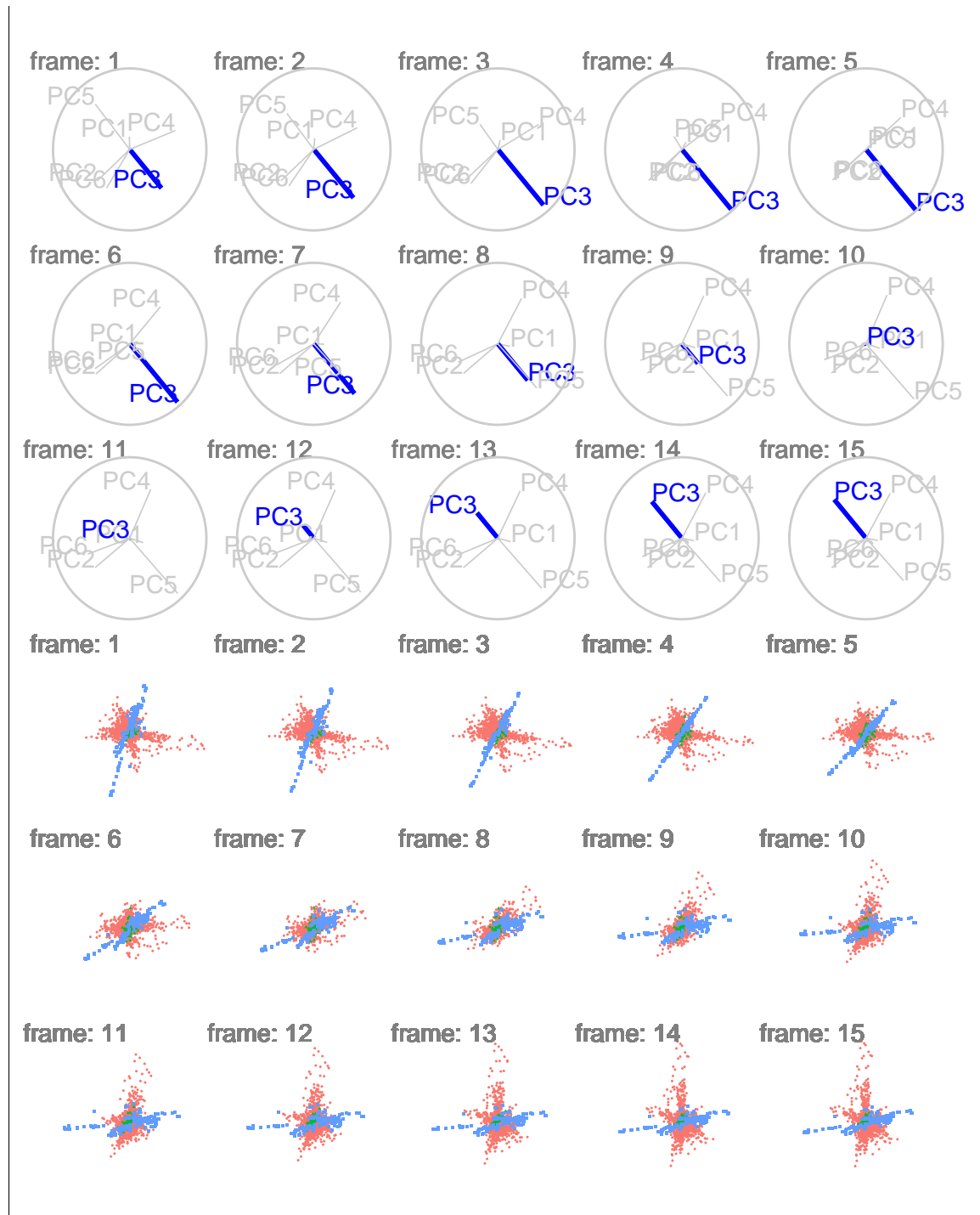


Figure 3.4: Manual tour of the PC6. First 6 principle components of select experiments with ‘dimuon SIDIS’ in green , ‘DIS HERA1+2’ experiments in black, and ‘charm SIDIS’ in red. Note that intermediate values of PC6 contain almost all of the information held within the green, dimuon SIDIS experiments

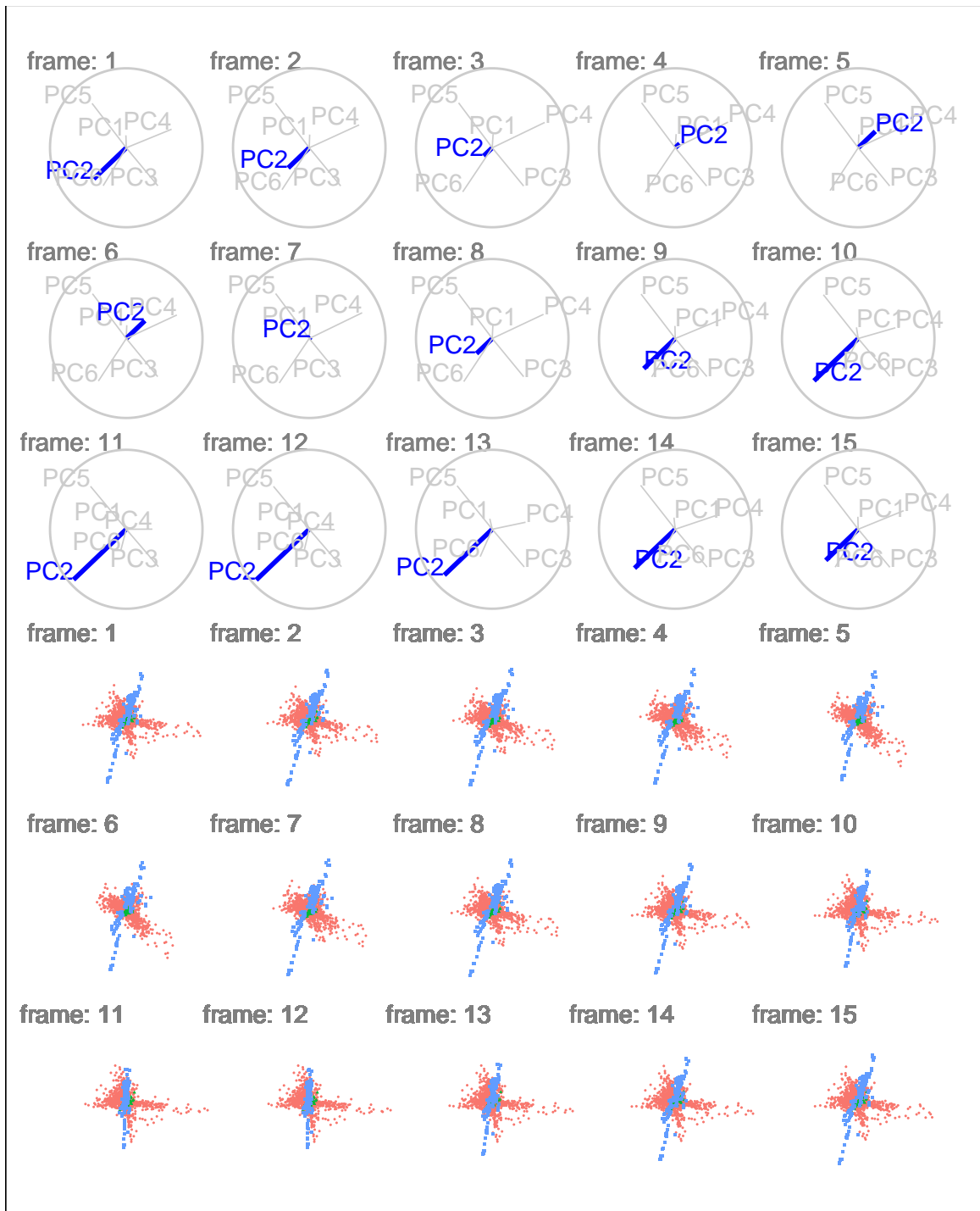


Figure 3.5: *FILL CAPTION HERE*

Dynamic version of this manual tour can be found at: https://nspyrison.netlify.com/thesis/discluster_manualtour_pc2/ The page take a bit to load as the .html object is large.

manip var (and link)	observation
PC1	obs
PC2	obs
PC3	obs
PC4	obs
PC5	obs
PC6	obs

3.5.2 Jet cluster

Manual tour of the first 4 principal components for experiments of ATLAS7old and ATLAS7new.

Manual tour on the PC3:

Dynamic version of this manual tour can be found at: https://nspyrison.netlify.com/thesis/jetcluster_manualtour_pc3/. The page take a bit to load as the .html object is large.

Manual tour on the PC4:

```
## [1] "n_slides < 15 decrease angle."
```

Dynamic version of this manual tour can be found at: https://nspyrison.netlify.com/thesis/jetcluster_manualtour_pc4/ The page take a bit to load as the .html object is large.

manip var (and link)	observation
PC1	obs
PC2	obs

<hr/>	
manip var (and link)	observation
<hr/>	
PC3	obs
PC4	obs
<hr/>	

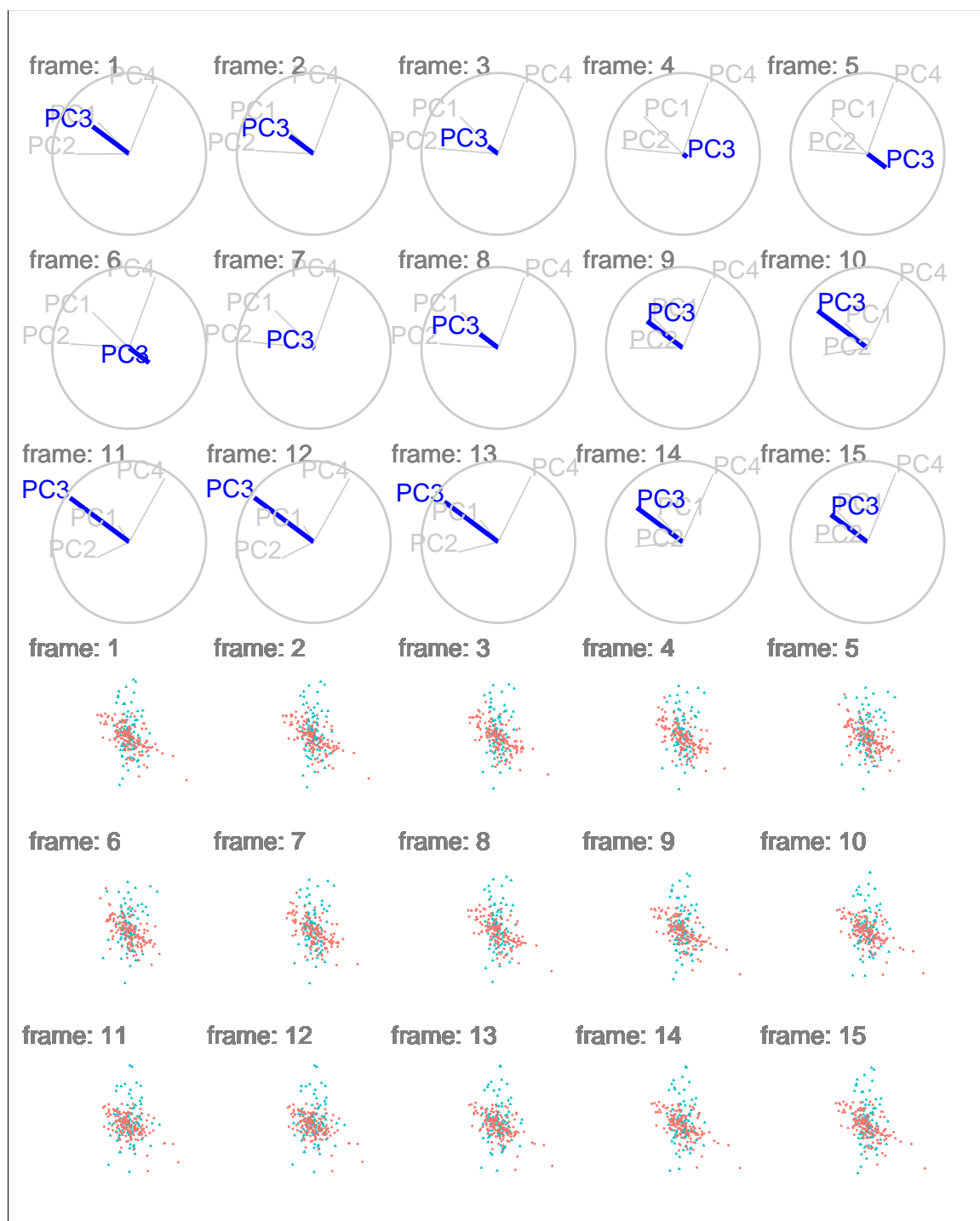


Figure 3.6: *FILL CAPTION HERE*

3.6 Source code and usage

This article was created bookdown (Xie (2016)) using rmarkdown (Xie, Allaire, and Grolmund (2018)), with code generating the examples inline, and the source files can be found at github.com/nspyrison/confirmation/.

The source code for the `spinifex` package can be found at github.com/nspyrison/spinifex/. To install the package in R, run:

```
# install.packages("devtools")  
devtools::install_github("nspyrison/spinifex")
```

3.7 Discussion

Future work:

- other rotation mechanisms like Givens and Householder
- oblique should be defined.
- other display types, would work for 1D displays, but others would need redefinition difference dimensions
- shiny app, for choosing manip variable, providing different starting projections

Chapter 4

Display dimensionality

- XGobbi vs the C2

Chapter 5

Human-computer interaction of 3d projections

- Tour in 3D
- ImAxes / IATK

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