

Interrogating the linear variable importance of local explanations of black-box models with animated linear projections

Abstract

Artificial Intelligence (AI) has seen a revitalization in recent years from the use of increasingly hard-to-interpret black-box models. In such models, increased predictive power comes at the cost of opaque factor analysis, which has led to the field of eXplainable AI (XAI). XAI attempts to shed light on these models, one such approach is the use of local explanations. A local explanation of a model gives a point-estimate of linear variable importance in the vicinity of one observation. We extract explanations for each observation, and approximate data and this attribution space side-by-side with linked brushing. After identifying an observation of interest its local explanation is used as a 1D projection basis. We then manipulate the magnitude of the variable contributions with a technique called the tour. This tour animates many projections over small changes in the projection basis. Doing so allows a user to visually explore the data space through the lens of this local explanation and interrogate its variable importance. The implementation of our framework is available as an **R** package **cheem** available at github.com/nsprison/cheem.

1 Introduction

Mathematically rigorous approaches to predictive modeling are attributed to the method of least squares, over two centuries ago by Legendre and Gauss in 1805 and 1809 respectively. In 1886 Francis Galton coined the term *regression* to refer to continuous, quantitative predictions. While *classification* refers to discrete predictions as introduced by Fisher in 1936.

Breiman and Shmueli (Breiman 2001; Shmueli 2010) introduce the idea of distinguishing modeling based on its purpose; *explanatory* modeling is done for some inferential purpose such as hypothesis testing, while *predictive* modeling is performed to predict new or future out-of-sample observations. This distinction draws attention to the divide between interpretable models and black-box models. In explanatory modeling, the interpretable is a key feature for drawing inferential conclusions. While predictive modeling may opt for potentially more accurate black-box models. The intended use of a model has important implications for which methods are used and the development of those models.

Black-box models are becoming increasingly common, but not without their share of controversy and issues (O’neil 2016; Kodiyani 2019). Applications have been known to reflect common biases against sex (Dastin 2018; Duffy 2019), race (Larson et al. 2016), and age (Díaz et al. 2018). Such issues occur when biases existent in the training data, the model picks up on this influence on the response variable which is then built into the model. Another issue is that of data drift when new data is outside the support of latent or exogenous explanatory variables. Data drift can lead to worse predictions (Lazer et al. 2014; Salzberg 2014). Such issues highlight the need to make models fair, accountable, ethical, and transparent which has led to the movement of XAI (Adadi and Berrada 2018; Arrieta et al. 2020).

One branch of XAI is local explanations, which take a variable attribution approach to bring transparency to a model. Local explanations attempt to approximate linear variable importance at the location of one observation. There are many such local explanations, any of which works with our approach (assuming model-explanation compatibility).

To illustrate our work we apply the model-agnostic explanation SHAP (Strumbelj and Kononenko 2010; Štrumbelj and Kononenko 2014). The exact details of SHAP are tangent to the ideas of this work, but suffice it to say that SHAP approximates variable importance by taking the median importance over permutations

of the explanatory variables. To be exact we apply a variant that enjoys a lower computational complexity, known as tree SHAP (S. M. Lundberg, Erion, and Lee 2018).

In multivariate data visualization a *tour* (Asimov 1985; Buja and Asimov 1986; S. Lee et al. 2021) is a sequence of linear projections of data onto a lower-dimensional space, typically 1-3D. Tours are viewed as an animation over small changes to the projection basis. Structure in a projection can then be explored visually to see which variables contribute to the formation of the structure. The intuition is similar to watching the shadow of a hidden 3D object change as the object is rotated; watching the structural shape of the shadow change gleans insight into the shape and features of the object.

There are various types of tours, which are distinguished by the sequence of projection bases. In a *manual* tour (Cook and Buja 1997; Spyrisson and Cook 2020) this path is defined by changing the contribution of a selected variable. Applying tours to models has been done in a couple of contexts. Specifically for exploring various statistical model fits and classification boundaries (Wickham, Cook, and Hofmann 2015), and using tree- and forest-based approaches as a projection pursuit index to generate a tour basis path (Y. D. Lee et al. 2013; Silva, Cook, and Lee 2021).

The approach purposed below is to use the manual tour as means to interrogate a local explanation; a means of evaluating if its variable importance is a good explanation for the model predictions. We provide a free and open-source R package `cheem` with an interactive application to facilitate analysis. By viewing approximations of data- and attribution-space side-by-side, with linked brushing an analyst can identify observations of interest whose explanations are then rendered at the initial projection basis and explored with a manual tour to further interpret the variable importance of the local explanation. We give case studies of toy and modern datasets for both classification and regression tasks.

The change in the projection basis might feel similar to counterfactual, what-if analysis, such as *Ceteris paribus* (Biecek 2020). Latin for “other things held constant” or “all else unchanged,” is a counterfactual analysis showing how an observation’s prediction would change from a change in one explanatory variable given that other variables are held constant. It ignores correlations of the variables and imagines a case that was not observed. In contrast, our approach is a geometric explanation of the factual observed case by varying the basis, the angle of the data object. Another difference is that the basis is restricted on orthonormality. That is to say when the contribution of one variable decreases the contributions of others necessarily increases such that there is a full component in that direction.

The rest of this paper is organized as follows. The next section **Local explanation statistics** covers the background of the local explanation SHAP and the traditional visuals produced from it. **Tours and the radial tour** digs deeper into the animation and what it shows. The section **Application Design** discusses the layout of the application, how it facilitates analysis, and discusses the backend details of the package and preprocessing. The section **Case Studies** illustrates several applications of this method. We conclude with a **Discussion** of the insights we draw from classification and regression tasks.

2 Local explanation statistics

Consider a highly non-linear model. At face value it is hard to say which variable(s) are sensitive to crossing of classification boundary or identify which variables caused an observation to have a relatively extreme residual. Local explanations shed light on these cases by approximating linear variable importance in the vicinity of one observation.

Figure 6 of Arrieta et al. (2020) gives a broad summarization of the taxonomy and literature of explanation techniques. This includes a large number of model-specific explanations such as deepLIFT, (Shrikumar et al. 2016; Shrikumar, Greenside, and Kundaje 2017) a popular recursive method for estimating importance in neural networks. There are a few number of model-agnostic explanations, of which LIME, (Ribeiro, Singh, and Guestrin 2016) SHAP, (S. Lundberg and Lee 2017) and their variants are popular.

These instance level explanations are used in a variety of ways depending on the data. In images saliency maps overlay or offset a heatmap indicating which pixels were important (Simonyan, Vedaldi, and Zisserman 2014). For instance, or the presence of snow may be highlighted when distinguishing if a picture of contains a

wolf or husky. In text analysis, Word-level contextual sentiment analysis can be used to highlight sentiment and magnitude of influential words (Vanni et al. 2018). In the case of numeric regression, they can be used to explain variable additive contributions from intercept to prediction (Ribeiro, Singh, and Guestrin 2016).

2.1 SHAP and tree SHAP

SHaply Additive exPlanations (SHAP) approximates the variable importance in the vicinity of one observation by taking the median importance of a subset of permutations in the explanatory variables. This idea stems from the field of game theory where Shapley devised a method to evaluate an individual’s contribution to cooperative games by permuting the players that contribute to the score (Shapley 1953).

To illustrate SHAP and its original use, explaining the difference between the intercept and an observation’s prediction, we use soccer data from FIFA 2020 season (Leone 2020). We have 5000 observations of nine skill measures (after aggregating variable with high correlation). A random forest model is fit to regress the log wages, in 2020 Euros, from the skill measures. We then extract the SHAP values of a star offensive player (L. Messi) and defensive player (V. van Dijk). We expect to see a difference in the attribution of the variable importance across the two positions of the players.

Figure 1 shows the SHAP values of these players. Panel a) shows these players receive a sizable difference in wages. Panel b) shows the underlying distribution of the SHAP attributions while permuting the explanatory variables, with the medians being the SHAP values. In the light of the player position, the difference in the variable importance makes sense; offensive and movement are more important for the offensive player, while defensive and power skills are more important to the model for explaining the prediction of the defensive player. We would likewise expect the profile of variable importance to be unique for star players of other positions as well, such as goalkeepers or middle fielders. Panel c) shows a simplified breakdown plot (Gosiewska and Biecek 2019), where a local explanation is used to additively explain the difference from the intercept to the observations prediction. Such additive approaches will show an asymmetry with respect to the variable ordering, so we opt to fix the order to that of panel b), namely, by decreasing the sum of the SHAP values.

In summary, this highlights how local explanations bring interpretability to a model at least in the vicinity of their observations. In this instance, we showed how two very different soccer players receive different profiles of variable importance to explain the prediction of their wages. In the following section, we will be using normalized explanations as the starting projection basis to interrogate the explanation further.

3 Tours and the radial tour

TODO:XXX

4 Application design

Below we illustrate the two primary displays of the application: the global view and the tour view. Then we’ll cover what we take away from the classification and regression tasks. Lastly, we discuss the preprocessing that needs to be done before display.

4.1 Classification task

What information do we glean from using this method on a classification task? Typically we select a misclassified observation in comparison with a correctly classified point that is nearby in data space. We start by seeing the data projected through the linear attribution, the combination that best justifies that prediction. By default, the manual tour varies the contribution of the variable with the largest difference between the primary and comparison observation. That is, we can test the sensitivity of each variable to structure identified by the local explanation, we are exploring the support of the explanation, evaluating the support or robustness of the prediction.

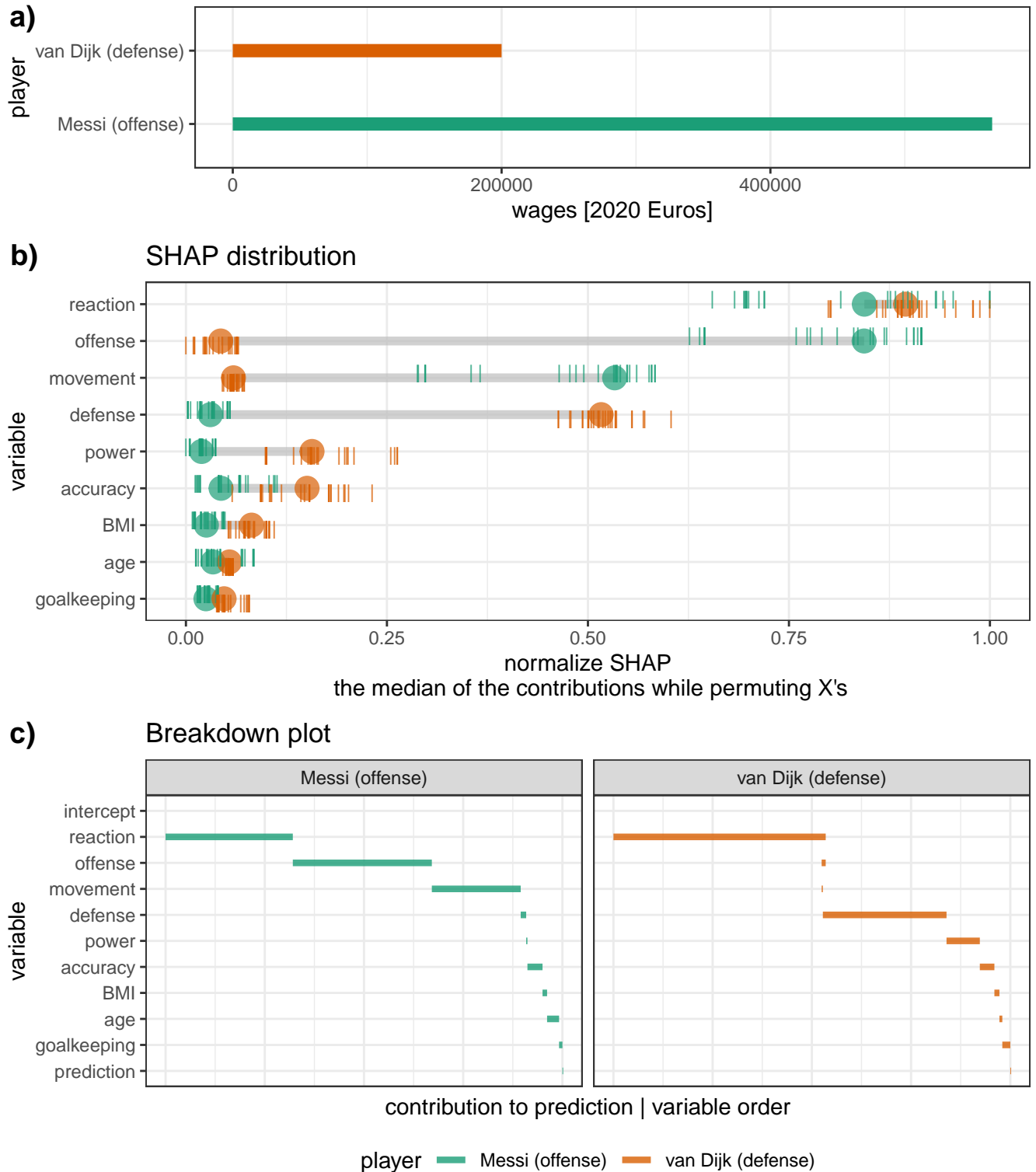


Figure 1: Illustration of the distribution of SHAP attributions and a breakdown plot. From FIFA 2020 data, a random forest model regresses wages from 9 skill attributes for a star offensive and defensive player. a) The players have very different wages. b) Shows the distributions of the attributions permuting over 25 permutations in the explanatory variables. The median of these distributions are the final SHAP values. The variable importance differs across the exogenous information of player position. These explanations make sense; the variable importances make sense in light of the position of the player. c) Breakdown plots of the observations the explanation used to additively explain the difference between the intercept and prediction

4.2 Regression task

The regression case is not as discrete a feature. Instead, we find it more meaningful to compare the observed value or residual with the projection. In this case the horizontal positions are the same, that is projection of the data through the attribution of the explanation and then varying as the radial tour changes the contributions of the selected variable. While the height of the points is fixed to the fixed either to the observed y and residuals for the middle and right panels respectively.

4.3 Global view

The global view is an important context for exploring the separability of the data- and the local explanation’s attribution-spaces, and is crucial in the selection of explanation to further interrogate and explore the structural sensitivity of.

We show an approximation of these spaces with a projection through their first two principal components. The orientation of the variables is shown inscribed on a unit circle. While a single 2D projection will rarely encompass all of the structure of higher-dimensional spaces, it provides a reasonable starting point for the real task at hand, the selection of observation and nearby comparison.

It is insightful to explore these two approximations against a visual of the model; prediction by observation is added. Linked brushing and preserved aesthetic features such as circling misclassified observations help link information from the different spaces together.

This view offers dynamic interaction in several ways. A tooltip displays while the cursor hovers over a point displays the row number/name and classification information if appropriate. Linked brushing allows for the selection of points (by click and drag) where those points will be highlighted in both plots. The information corresponding to the selected points is populated on a sortable table and the data powering the proceeding tour will also subset the data to the current selection.

4.4 Cheem tour

The primary observation identified via the global view is foundational to the production of the cheem tour. Namely, the linear attribution of that variable is used as a 1D projection basis. This is the approximate contribution of the variables that this model uses to justify its prediction for the observation.

The SHAP values of the full dataset are shown as horizontal parallel coordinate plots at the top with the selected observations highlighted. In the classification case, 1D density curves with underlying rug marks are drawn and colored according to their predicted classes. In the regression case, the horizontal position of the points comes from projection through the 1D attribution basis while the vertical position is fixed to the observations prediction and residual respectively. The current projection basis is depicted on the bottom, where the width of a bar is mapped to the variable’s contribution to the horizontal axis. The starting frame is the normalized SHAP values of the primary observation. In figure 3 we illustrate the classification case with simulated data; 3 clusters separated in the first 2 dimensions with 2 dimensions of noise.

Data visualization tours animate many linear projections over small changes to the basis. The manual tour creates a basis path by varying the contribution of a selected variable, fully into and out of a projection frame. Doing allows an analyst to test an individual variable’s sensitivity to the structure identified in the frame. The default variable selected is the one with the largest discrepancy between the primary and comparison observation’s attribution. In the following sections we elaborate on the takeaways we draw from applying this approach in classification and regression tasks respectively.

In the regression case, we compare an observation with a particularly extreme residual as compared with a neighboring point that is more accurately predicted. The global tour is primarily the same without the misclassified circles, but the tooltip now shows the observation’s residual. We simulate data, five variables from the uniform distribution in the support $[0, 5]$ and $y = x_1 + x_2 + x_1 * x_2 + (x_3 + x_4 + x_5)/10 + \epsilon$. We fit a random forest and extract the tree SHAP values from all observations. The first thing we notice from the global view is the shape difference between the data- and attribution-spaces, which are primarily circular are triangular respectively. We also see that the random forest fit the data quite well viewing the predictions

Global view: PC1:2 approximations of data- and attribution-spaces

Primary observation rownum, ('*' point):

18

Comparison observation rownum, ('x' point):

119

Color and shape are mapped to the predicted species of the penguin. This was also the target variable of the RF model.

Red circle around the point indicates a misclassified point.

Selection: click & drag to select points, double click to remove the selection.

-- Selecting points will highlight them in all facets and display detailed information below.

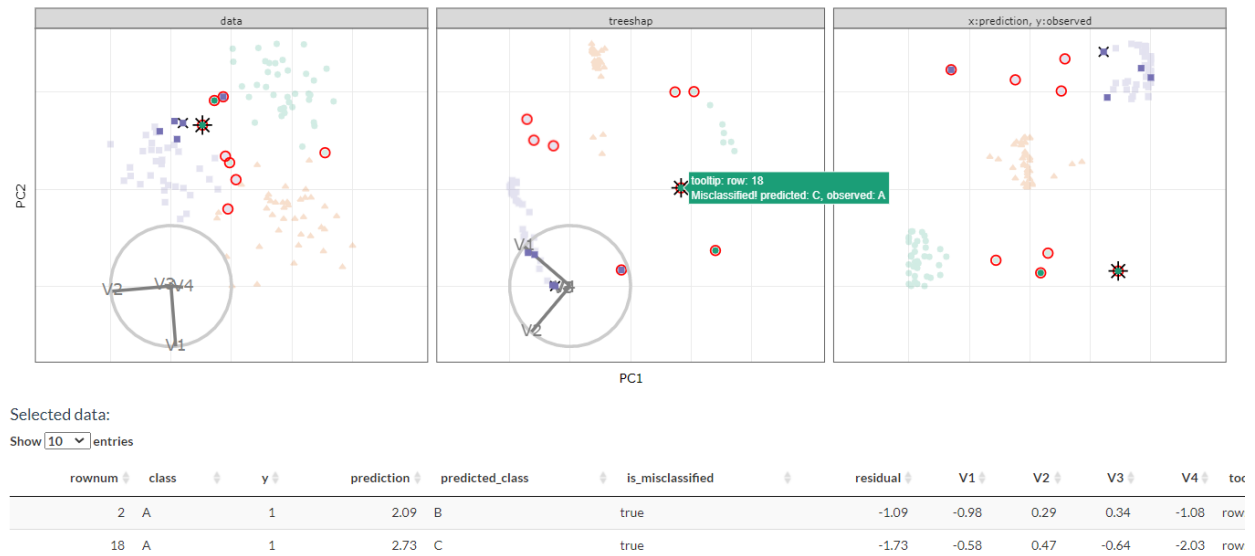


Figure 2: Global view screen capture; the approximations of the data and SHAP-spaces of Palmer penguins data. Orientation of the basis contributions is illustrated on a unit circle. Linked brushing allows observations brushed in one plot to be selected in others. This selection is also used in the proceeding view and their corresponding information is displayed in an interactive table. Hovering the cursor over an observation displays a tooltip with row number/name information. In the classification case, misclassified points are circled in red. This view provides an orientation to select a primary and comparison observation, key targets in the following tour.

Cheem tour

The data-space projected through normalized attribution of the primary observation.

Inclusion variables

☒ V1 ☒ V2 ☒ V3 ☒ V4

Manipulation variable:

V2

Draw PCP lines on the basis
distribution?

Yes

Solid grey line/: true zero, all X 's = 0 projected through the basis.

Longer-dashed and dotted lines: location of primary & comparison observations respectively ('*/'x' in global view).

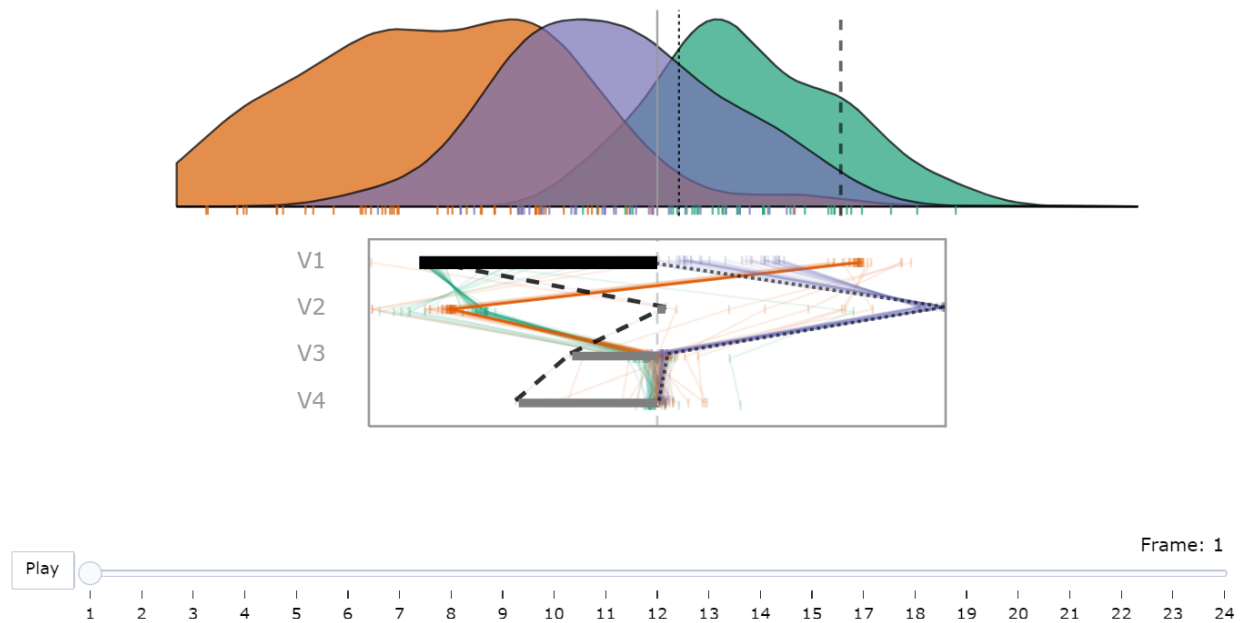


Figure 3: Cheem tour, classification case. A random forest model predicting the class of the of simulated data. A misclassified observation is be compared with a nearby correctly classified observation. The top shows density and rug marks of the current frame with the positions of the primary and comparison observations shown as dashed and dotted lines. The bottom shows two key features; the distribution of attribution space shown as parallel coordinate lines across the variables and the bars show the current contribution of the variable to the projection. The primary, misclassified observation (dashed line), is plausibly in the middle of the its prediction, purple density, the story that the explanation trying to sell us. Yet, when we play the tour animating on the contribution of V1, the bottom dashed line is more regularly in the center the it observed cluster, green, By varying this contribution we gain information of how sensitive this variable is to the explanation; the variable importance which led to a misclassification.

across the observations. Though linked brushing we find that the attribution space is highly correlated with the y value. The highest values occupy one corner of the triangle, the lowest values cluster on the opposite side, and the middle values form a ‘)’ shape filling out the triangle in attribution space. In the regression case, the tour view is a bit different, this is illustrated in figure 4. The current frames basis and distribution are shown to the left. The horizontal positions of the two scatter plots are the resulting 1D projection of the basis while the heights are fixed to the observed y and the residuals.

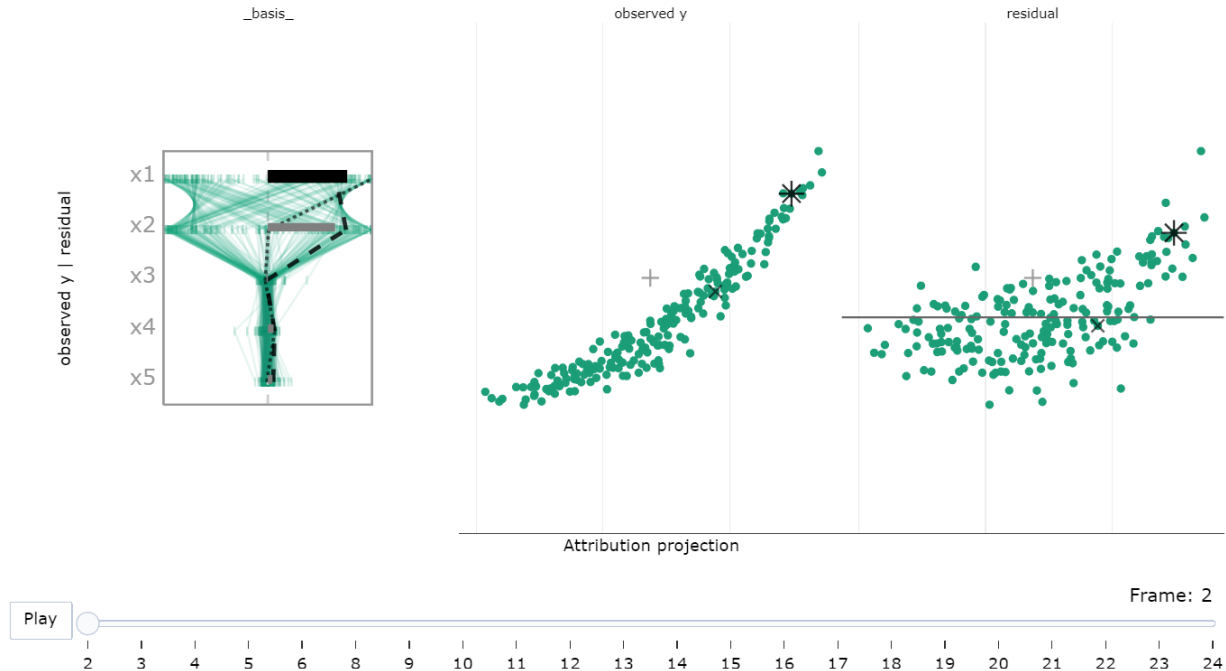


Figure 4: Cheem tour, regression case. A random forest model predicting the continuous y of the of simulated data where $y = x1 + x2 + x1 * x2 + (x3 + x4 + x5)/10 + \epsilon$. The current frames basis and the distribution of all attributions is shown on the left. The horizontal positions for the scatterplots are resulting projection through the 1D basis while the vertical heights are fixed to the observed y and residuals respectively.

Now that we have covered the classification and regression cases we will discuss the preprocessing, package infrastructure, and interactive features before proceeding to case studies with data from the wild.

4.5 Interactive features

The dynamic interaction with the global view is critical to the selection of the primary and comparison observations. Linked brushing also for a rectangular selection of observations. These points are highlighted within the other space of the global view *and* crucially available for downstream consumption, for instance, highlighting in the tour. The distinction between the former and latter is subtle, but important for developers to grasp. In the former, self-contained HTML widgets can highlight directly within javascript without evaluation downstream in other reactive functions. In the latter, the use of `plotly::event_data()` returns the identity of the selected observations. This will require a reactive flush, but after that, the sky is the ceiling.

4.6 Preprocessing

The benefit of having dynamic interaction with data is predicated on a reasonably small render time. It is important to preprocess as much work as possible so that application resources can be used efficiently. The work remaining at runtime should be solely responding to inputs and the rendering of figures and tables. Below we discuss the steps and details of the preprocessing.

- **Data:** a complete numerical matrix; explanatory and response variable, an optional aesthetic variable (color/shape) can be mapped typically a categorical variable.
- **Model:** any model can be used with this method. Currently, we apply random forest models via the package **randomForest** (Liaw and Wiener 2002) to mitigate the runtime of our local explanation which requires tree-based models.
- **Local explanation:** any model-compatible linear explanation could be used. We apply tree SHAP, a more computationally efficient variant of SHAP applicable to tree-based models. This is done with the package **treeshap** (Kominsarczyk et al. 2021), hosted on GitHub only]. The global view shows all observations in attribution space requiring that we must extract the variable weightings from *all* observations rather than just one. <!--
- **Global view:** The data- and attribution-spaces are approximated as their the first two principal components. -->

The time to preprocess the data will vary significantly with the choice of model and local explanation. For reference, the FIFA data, 5000 observations of 9 explanatory variables, took 2.9 seconds to fit a random forest models of modest hyperparameters. Extracting the tree SHAP values of each observation took 254 seconds combined. PCA and statistics of the variables and attribution took 0.6 seconds. These runtimes were from a non-parallelized R session on a modern laptop, but suffice it to say that the bulk of the time will be spent on the local attribution. This makes tree SHAP, with its reduced computational complexity a good candidate to start with. Alternatively, the package **fastshap** (Greenwell 2020) claims extremely low runtimes which are attributed to fewer calls to the prediction function, partial implementation in C++, and efficient use of logical subsetting.

4.7 Package infrastructure

The above-described method and application are implemented as an open-source **R** package, **cheem** *TODO:XXX include cran URL after published*. Preprocessing was facilitated with models created via **randomForest** [liaw_classification_2002], and explanations calculated with **treeshap** (Kominsarczyk et al. 2021). The application is made with **shiny** (Chang et al. 2021). The tour visual is an extension of **spinifex** (Spyrison and Cook 2020). Both views are created first with first with **ggplot2** (Wickham 2016) and then rendered as interactive HTML widgets with **plotly** (Sievert 2020). **DALEX** (Biecek 2018) and the free ebook, *Explanatory Model Analysis* (Biecek and Burzykowski 2021) was a huge boon to understanding local explanations and how to apply them.

Installation and get started with the package can be acheived by running the following in **R**:

```
## Download the package:
install.packages("cheem", dependencies = TRUE)
library("cheem")
## Try the app:
run_app()
## Bring your own data: follow the examples in cheem_ls()
?cheem_ls
```

5 Case studies

To illustrate the use of the cheem method we apply it to modern datasets, two classification examples and then two of regression.

5.1 1) Penguin, species classification

Palmer penguins data (Gorman, Williams, and Fraser 2014; Horst, Hill, and Gorman 2020) consist of 330 observations across four physical measurements of three species of penguins foraging near Palmer

Station, Antarctica. A random forest model was fit, classifying the species of the penguin given the physical measurements.

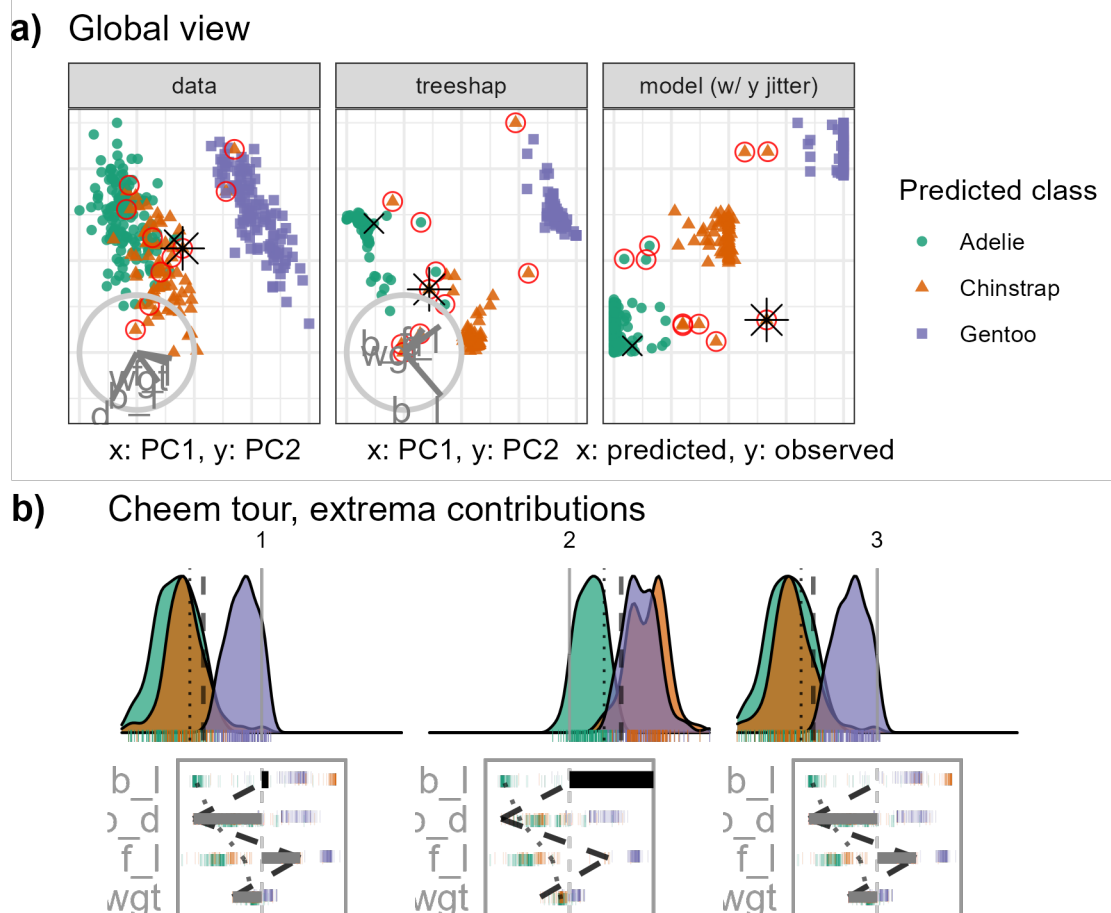


Figure 5: Species classification of Palmer penguin data.

In figure 5 a misclassified point is contrasted with a correctly classified point of its observed class that is nearby in data-space. The attribution space from the treeshap local explanations is a more separable space, where the comparison is squarely in the middle of the orange distribution while primary observation is in-between the predicted and observed clusters, a sign of uncertainty in the prediction. The tour varies the contribution of bill length (b_l) as this variable differs most from the contribution of the comparison observation. Downplaying the contribution of bill length is crucial to linear explanation this observation be misclassified.

5.2 2) Chocolates, milk/dark chocolate classification

The chocolates dataset consists of 88 observations of 10 nutritional measurements from their labels. Each of which was labeled as being either milk or dark chocolates. With this data, we can see if a manufacturer is giving an accurate portrayal of the chocolate. We are curious to see if there are chocolates that nutritionally look like milk chocolates that are labeled as dark chocolates, which may hold a higher market value. We should note that not all chocolates consist wholly of chocolate. The addition of other ingredients will decrease the predictive power of the model nutritional explanatory variable. A random forest model is fit classifying the type of chocolate. We select a chocolate labeled dark, through predicted to be milk chocolate with a comparison with a chocolate labeled 85% cocoa.

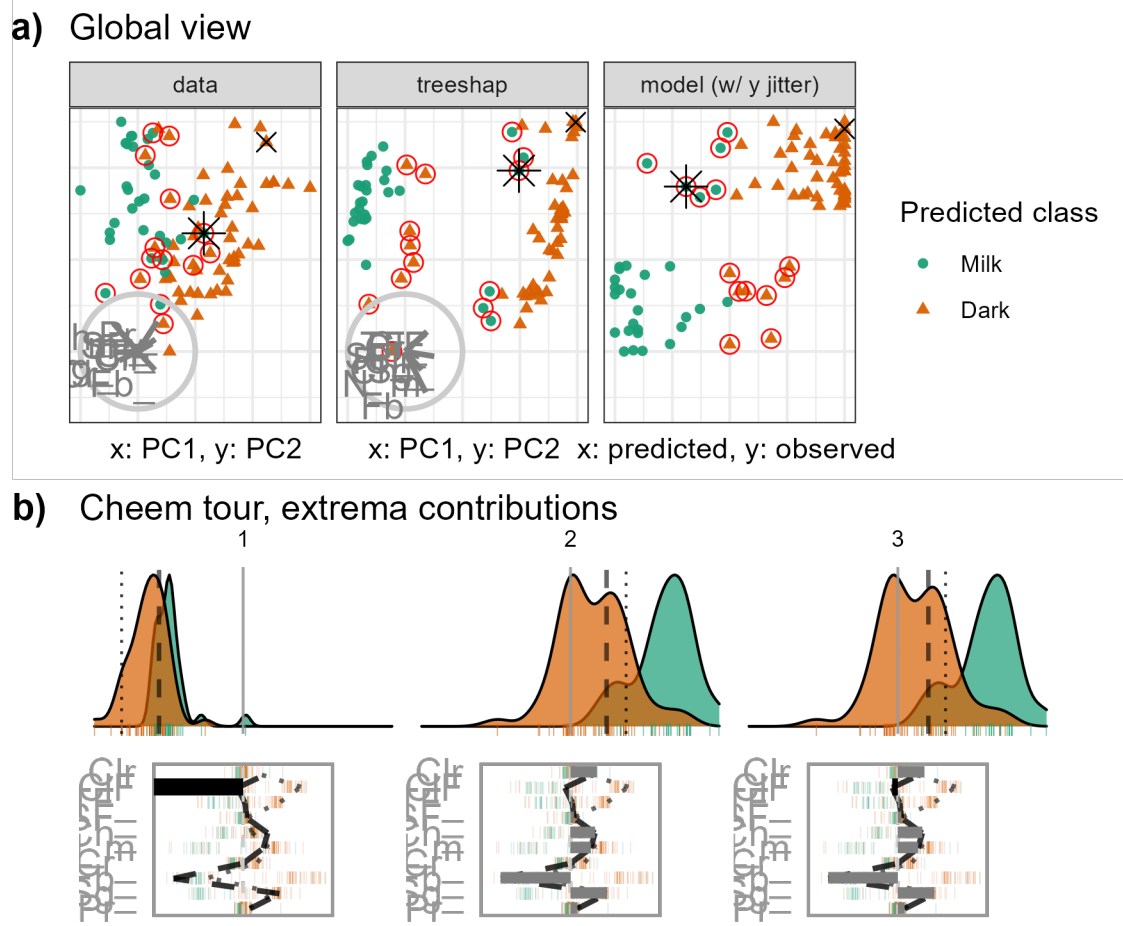


Figure 6: Chocolates data type classification (milk or dark).

From figure 6 we similarly see that attribution space that is more separable relative to data-space. Interestingly there is not the class imbalance that we suspected; there are only 6 chocolates labeled as dark and predicted as milk, while there 8 of the inverse case. Calories from fat is the measure with the largest difference in treeshap attribution between these points.

5.3 3) FIFA, wage regression

The 2020 season FIFA (Leone 2020; Biecek 2018), contains many skill measurements of soccer/football players along with wage information. After aggregation of the skill measurements, we regress the log wages [2020 euros] given just the skill aggregates. The model was fit with 5000 observations of the 9 skill aggregates before being thinned to 500 players to gate occlusion and render time. We compare a leading offensive fielder (L. Messi) with that of a leading defensive fielder (V. van Dijk), the same observations used in figure 1.

With figure 7 we are going to test the premise of the local explanation. If we remove reaction and movement skills from the basis, then offense has almost singular importance for the explanation of the offensive player. We vary the contribution of offensive skills. In the tour (3rd frame of b), offensive skills moved, and Messi is no longer separated from the group. We also notice that accuracy has rotated into the frame, which does maintain some separability.

5.4 4) Ames housing prices 2018

Ames 2018, housing data was subset to North Ames (the neighborhood with the most house sales). The remaining are 338 house sales across 9 variables. Using interaction from the global view we select a house with an extreme negative residual and an accurate observation close to it in the data.

Figure 8 shows the global view and extrema of the tour. The horizontal distance in the tour didn't show a large disparity between our selected points. This is not particularly surprising as most of the features have a sizable contribution. Rotating any one variable out of the frame will rotate other important variables into frame preserving most of the distance from intercept to prediction. However, the tour has revealed an interesting feature worth discussing. notice that the observations pivot about the origin, that is the basis roughly halfway between bases in frame 1 and 2 of panel b) the data is near a singular profile. This means that there is a basis orthogonal to this point that describes a lot of the variation. Knowing these singular frames can help direct to bases that have meaningful variation in the data.

6 Discussion

The need to maintain the interpretability of black-box models is clear. One way to do this is by the use of local explanations of an observation. Local explanations approximate the linear variable importance to the model. Our idea is to visualize approximations of the data and explanation spaces side-by-side, using dynamic interaction to compare and contrast, and ultimately, identify primary and comparison observations of interest. Then use the linear importance from the primary observation as a projection basis and explore a single variable's importance to the structure identified with the use of the manual tour.

We have illustrated this method on random forest models using the tree SHAP local explanation, while it could be generalized to any compatible model-explanation pair. We apply this to both the classification and regression tasks. In the former, it can be used to see which variables cause a misclassification as benchmarked against a nearby observation and explore changing the contribution of variables. In the regression case, we compare an observation with particularly extreme residual can be compared with nearby points more accurately predicted or another suitable benchmark.

We have created an open-source **R** package **cheem**, available on CRAN, to facilitate this workflow including a dynamic application, with the ability to upload preprocessed data.

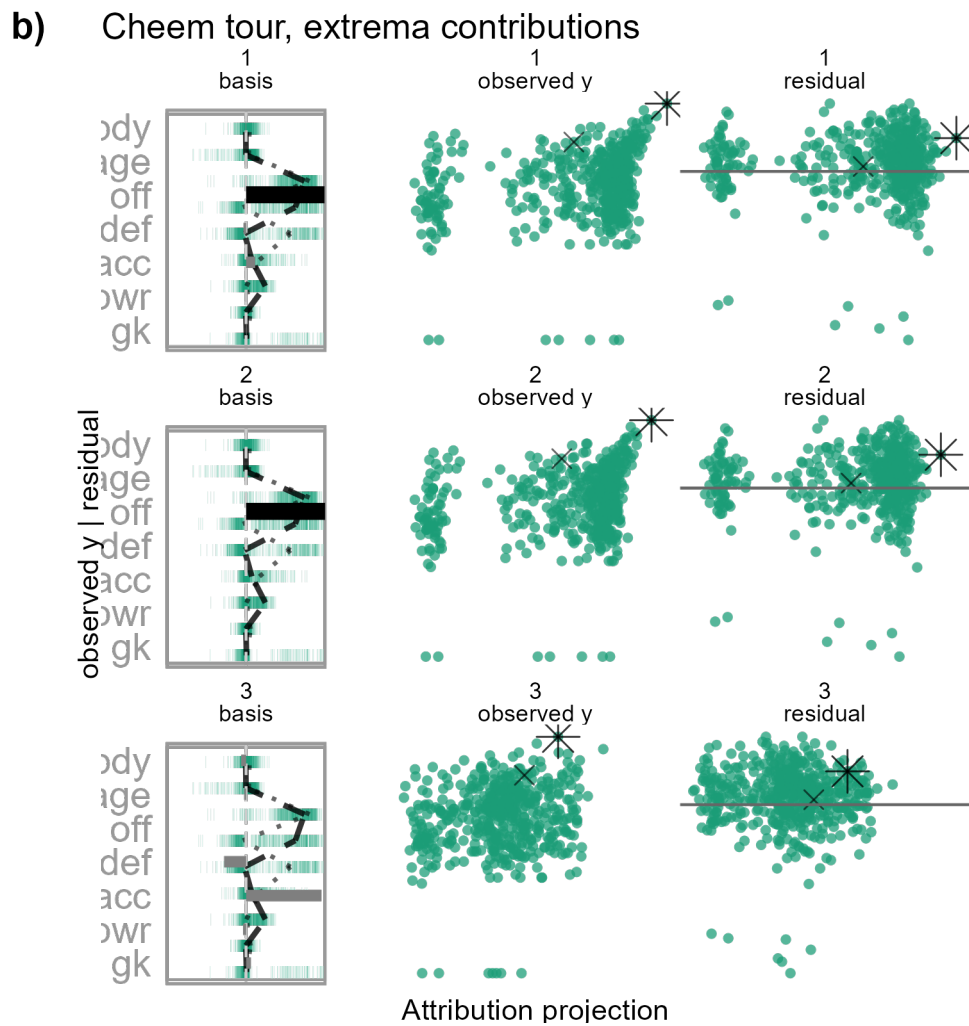
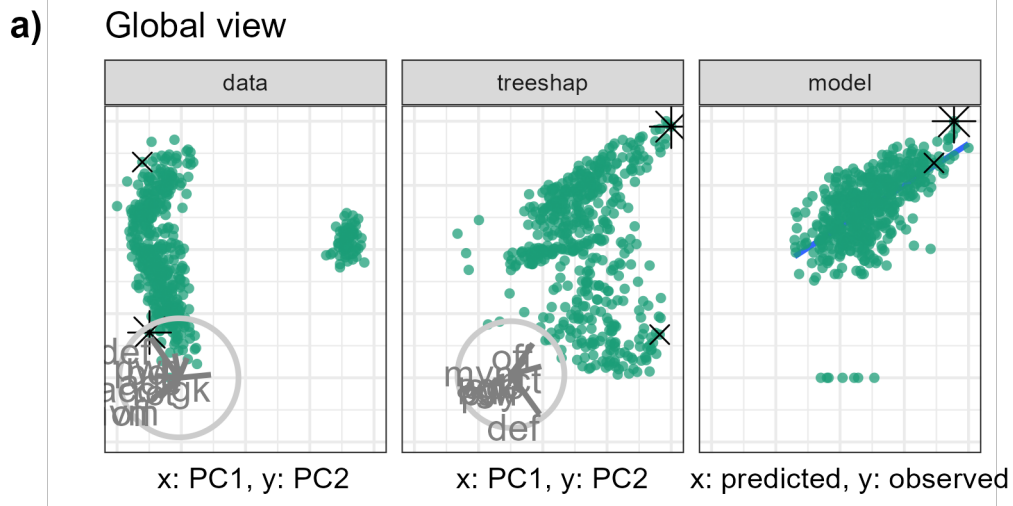
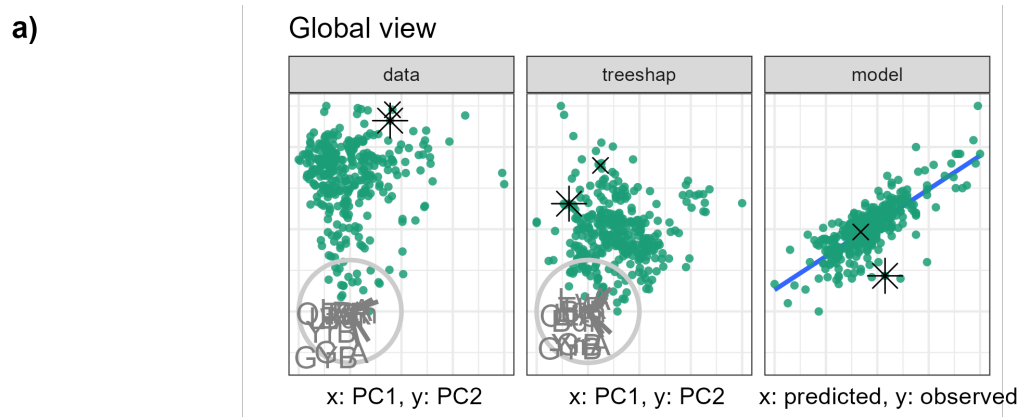


Figure 7: FIFA 2020, regressing log wages [2020 Euros] from aggregations of skill measurements. The primary observation is star offensive player (L. Messi) as compared with a top defensive player (V. van Dijk).



b)

Cheem tour, select frames

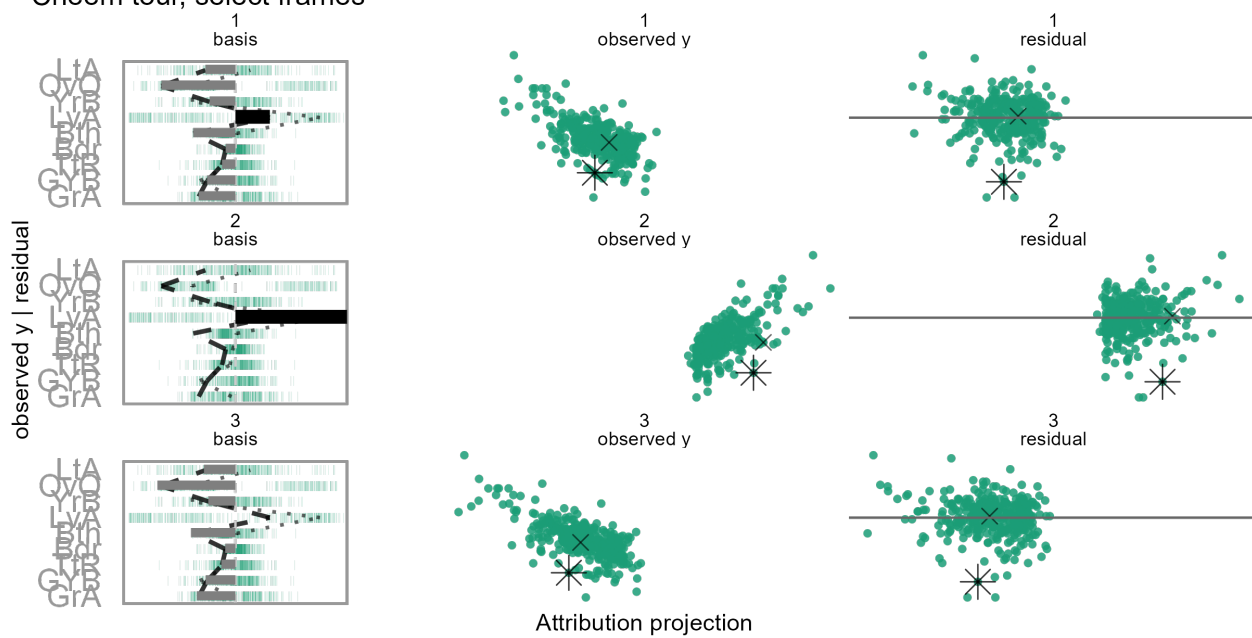


Figure 8: Ames housing 2018 regressing log sales price [2018 USD].

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We would like to thank Professor Przemyslaw Biecek for his input early in the project and to the broader MI² lab group for the **DALEX** ecosystem of **R** and **Pyhton** packages. This research was supported in part by Australian government Research Training Program (RTP) scholarships.

The namesake, Cheem, refers to a fictional race of humanoid trees in Doctor Who lore. **DALEX** pulls on from that universe and we originally apply tree SHAP explanations which are specific to tree-based models.

References

- Adadi, Amina, and Mohammed Berrada. 2018. “Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI).” *IEEE Access* 6: 52138–60.
- Arrieta, Alejandro Barredo, Natalia Díaz-Rodríguez, Javier Del Ser, Adrien Bennetot, Siham Tabik, Alberto Barbado, Salvador García, Sergio Gil-López, Daniel Molina, and Richard Benjamins. 2020. “Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges Toward Responsible AI.” *Information Fusion* 58: 82–115.
- Asimov, Daniel. 1985. “The Grand Tour: A Tool for Viewing Multidimensional Data.” *SIAM Journal on Scientific and Statistical Computing* 6 (1): 128–43. <https://doi.org/https://doi.org/10.1137/0906011>.
- Biecek, Przemyslaw. 2018. “DALEX: Explainers for Complex Predictive Models in R.” *The Journal of Machine Learning Research* 19 (1): 3245–49.
- . 2020. *ceterisParibus: Ceteris Paribus Profiles*. <https://CRAN.R-project.org/package=ceterisParibus>.
- Biecek, Przemyslaw, and Tomasz Burzykowski. 2021. *Explanatory Model Analysis: Explore, Explain, and Examine Predictive Models*. CRC Press.
- Breiman, Leo. 2001. “Statistical Modeling: The Two Cultures (with Comments and a Rejoinder by the Author).” *Statistical Science* 16 (3): 199–231.
- Buja, Andreas, and Daniel Asimov. 1986. “Grand Tour Methods: An Outline.” In *Proceedings of the Seventeenth Symposium on the Interface of Computer Sciences and Statistics on Computer Science and Statistics*, 63–67. New York, NY, USA: Elsevier North-Holland, Inc. <http://dl.acm.org/citation.cfm?id=26036.26046>.
- Chang, Winston, Joe Cheng, JJ Allaire, Carson Sievert, Barret Schloerke, Yihui Xie, Jeff Allen, Jonathan McPherson, Alan Dipert, and Barbara Borges. 2021. *Shiny: Web Application Framework for r*. <https://CRAN.R-project.org/package=shiny>.
- Cook, Dianne, and Andreas Buja. 1997. “Manual Controls for High-Dimensional Data Projections.” *Journal of Computational and Graphical Statistics* 6 (4): 464–80. <https://doi.org/10.2307/1390747>.
- Dastin, Jeffrey. 2018. “Amazon Scraps Secret AI Recruiting Tool That Showed Bias Against Women.” *Reuters*, October. <https://www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G>.
- Díaz, Mark, Isaac Johnson, Amanda Lazar, Anne Marie Piper, and Darren Gergle. 2018. “Addressing Age-Related Bias in Sentiment Analysis.” In *Proceedings of the 2018 Chi Conference on Human Factors in Computing Systems*, 1–14.
- Duffy, Claire. 2019. “Apple Co-Founder Steve Wozniak Says Apple Card Discriminated Against His Wife.” *CNN*, November. <https://www.cnn.com/2019/11/10/business/goldman-sachs-apple-card-discrimination/index.html>.
- Gorman, Kristen B., Tony D. Williams, and William R. Fraser. 2014. “Ecological Sexual Dimorphism and Environmental Variability Within a Community of Antarctic Penguins (Genus *Pygoscelis*).” *PloS One* 9 (3): e90081.

- Gosiewska, Alicja, and Przemyslaw Biecek. 2019. "IBreakDown: Uncertainty of Model Explanations for Non-Additive Predictive Models." *arXiv Preprint arXiv:1903.11420*.
- Greenwell, Brandon. 2020. *Fastshap: Fast Approximate Shapley Values*. <https://CRAN.R-project.org/package=fastshap>.
- Horst, Allison Marie, Alison Presmanes Hill, and Kristen B. Gorman. 2020. "Palmerpenguins: Palmer Archipelago (Antarctica) Penguin Data." <https://allisonhorst.github.io/palmerpenguins/>.
- Kodiyan, Akhil Alfons. 2019. "An Overview of Ethical Issues in Using AI Systems in Hiring with a Case Study of Amazon's AI Based Hiring Tool." *Researchgate Preprint*.
- Kominsarczyk, Konrad, Pawel Kozminski, Szymon Maksymiuk, and Przemyslaw Biecek. 2021. "Treeshap." Model Oriented. <https://github.com/ModelOriented/treeshap>.
- Larson, Jeff, Surya Mattu, Lauren Kirchner, and Julia Angwin. 2016. "How We Analyzed the COMPAS Recidivism Algorithm." *ProPublica*, May. https://www.propublica.org/article/how-we-analyzed-the-compas-recidivism-algorithm?token=RPR1E2qtzJltfJ0tS-gB_41kmfoWZAu4.
- Lazer, David, Ryan Kennedy, Gary King, and Alessandro Vespignani. 2014. "The Parable of Google Flu: Traps in Big Data Analysis." *Science* 343 (6176): 1203–5.
- Lee, Stuart, Dianne Cook, Natalia Da Silva, Ursula Laa, Earo Wang, Nick Spyrisson, and H. Sherry Zhang. 2021. "A Review of the State-of-the-Art on Tours for Dynamic Visualization of High-Dimensional Data." *arXiv Preprint arXiv:2104.08016*.
- Lee, Yoon Dong, Dianne Cook, Ji-won Park, and Eun-Kyung Lee. 2013. "PPtree: Projection Pursuit Classification Tree." *Electronic Journal of Statistics* 7: 1369–86.
- Leone, Stefano. 2020. "FIFA 20 Complete Player Dataset." <https://kaggle.com/stefanoleone992/fifa-20-complete-player-dataset>.
- Liaw, Andy, and Matthew Wiener. 2002. "Classification and Regression by randomForest." *R News* 2 (3): 18–22.
- Lundberg, Scott M., Gabriel G. Erion, and Su-In Lee. 2018. "Consistent Individualized Feature Attribution for Tree Ensembles." *arXiv Preprint arXiv:1802.03888*.
- Lundberg, Scott, and Su-In Lee. 2017. "A Unified Approach to Interpreting Model Predictions." *arXiv Preprint arXiv:1705.07874*.
- O'neil, Cathy. 2016. *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*. Crown.
- Ribeiro, Marco Tulio, Sameer Singh, and Carlos Guestrin. 2016. "'Why Should I Trust You?': Explaining the Predictions of Any Classifier." *arXiv:1602.04938 [Cs, Stat]*, February. <http://arxiv.org/abs/1602.04938>.
- Salzberg, Steven. 2014. "Why Google Flu Is A Failure." *Forbes*, March. <https://www.forbes.com/sites/stevensalzberg/2014/03/23/why-google-flu-is-a-failure/>.
- Shapley, Lloyd S. 1953. *A Value for n-Person Games*. Princeton University Press.
- Shmueli, Galit. 2010. "To Explain or to Predict?" *Statistical Science* 25 (3): 289–310.
- Shrikumar, Avanti, Peyton Greenside, and Anshul Kundaje. 2017. "Learning Important Features Through Propagating Activation Differences." In *International Conference on Machine Learning*, 3145–53. PMLR.
- Shrikumar, Avanti, Peyton Greenside, Anna Shcherbina, and Anshul Kundaje. 2016. "Not Just a Black Box: Learning Important Features Through Propagating Activation Differences." *arXiv Preprint arXiv:1605.01713*.
- Sievert, Carson. 2020. *Interactive Web-Based Data Visualization with R, Plotly, and Shiny*. Chapman; Hall/CRC. <https://plotly-r.com>.

- Silva, Natalia da, Dianne Cook, and Eun-Kyung Lee. 2021. “A Projection Pursuit Forest Algorithm for Supervised Classification.” *Journal of Computational and Graphical Statistics*, 1–21.
- Simonyan, Karen, Andrea Vedaldi, and Andrew Zisserman. 2014. “Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps.” In *In Workshop at International Conference on Learning Representations*. Citeseer.
- Spyrison, Nicholas, and Dianne Cook. 2020. “Spinifex: An R Package for Creating a Manual Tour of Low-Dimensional Projections of Multivariate Data.” *The R Journal* 12 (1): 243. <https://doi.org/10.32614/RJ-2020-027>.
- Strumbelj, Erik, and Igor Kononenko. 2010. “An Efficient Explanation of Individual Classifications Using Game Theory.” *The Journal of Machine Learning Research* 11: 1–18.
- Štrumbelj, Erik, and Igor Kononenko. 2014. “Explaining Prediction Models and Individual Predictions with Feature Contributions.” *Knowledge and Information Systems* 41 (3): 647–65.
- Vanni, Laurent, Mélanie Ducoffe, Carlos Aguilar, Frédéric Precioso, and Damon Mayaffre. 2018. “Textual Deconvolution Saliency (TDS): A Deep Tool Box for Linguistic Analysis.” In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 548–57.
- Wickham, Hadley. 2016. *Ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. <https://ggplot2.tidyverse.org>.
- Wickham, Hadley, Dianne Cook, and Heike Hofmann. 2015. “Visualizing Statistical Models: Removing the Blindfold.” *Statistical Analysis and Data Mining: The ASA Data Science Journal* 8 (4): 203–25. <https://doi.org/10.1002/sam.11271>.