Locally Interpretable Model-Agnostic Explanations

a.k.a LIME a.k.a WTF is my model doing

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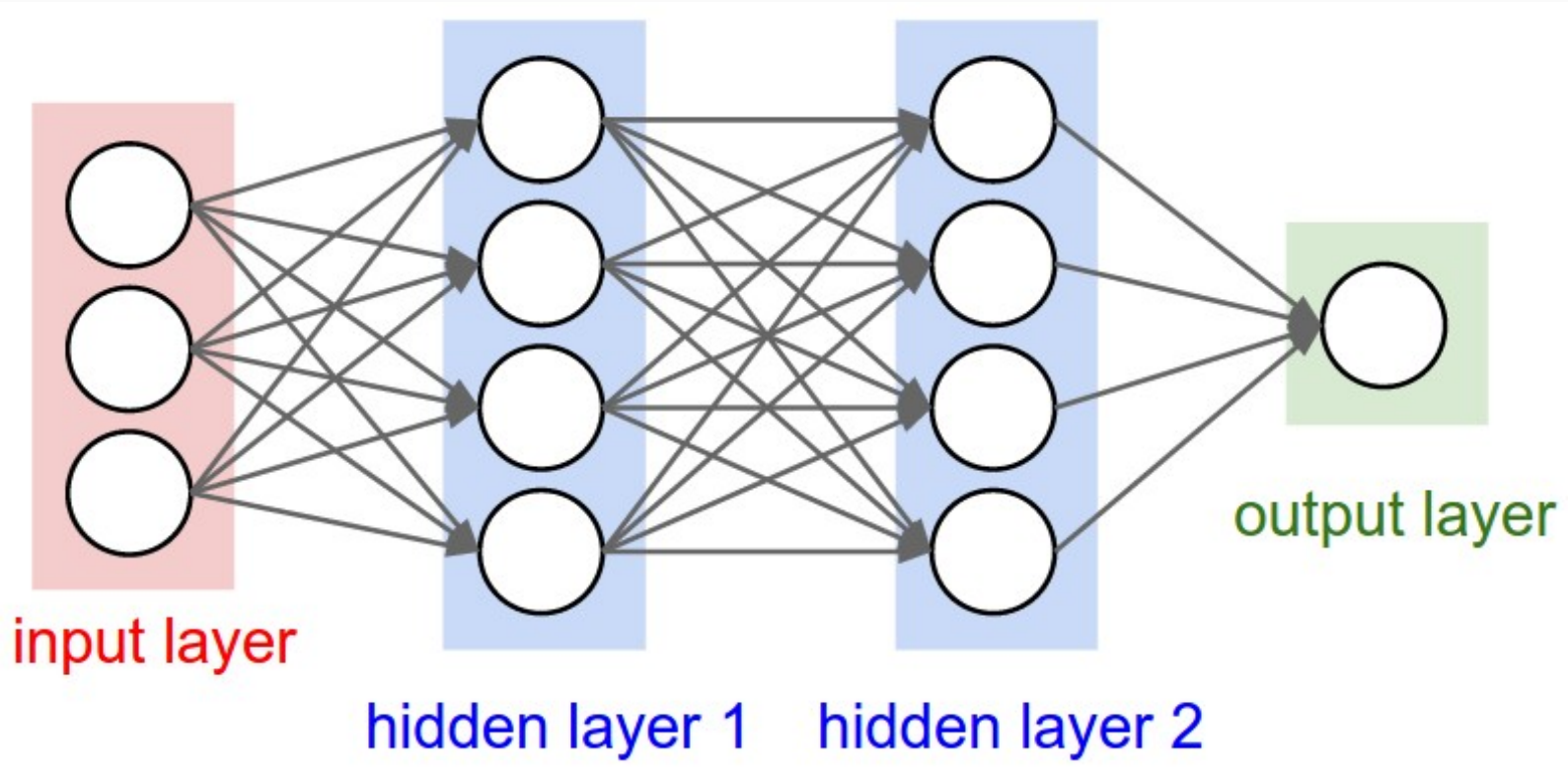
Motivation

- some models combine data in non-linear ways
- still want to know what's going on



How to explain a model where f is complex?

$X \in \mathbb{R}^{n,p}$ is a data matrix of n points in p space
$f : \mathbb{R}^p \to \{1, 2, ..., K\}$ is a classification model

1. Create a binarized and interpretable version of data (called X')
2. Approximate f locally with an interpretable model fit to X'

Multiclass classification treated as K binary classification problems, K the number of classes

Creating interpretable data X'

Original:

```
## # A tibble: 6 x 5
##   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
##          <dbl>       <dbl>        <dbl>       <dbl> <fct>
## 1          5.1         3.5          1.4         0.2 setosa
## 2          4.9         3            1.4         0.2 setosa
## 3          4.7         3.2          1.3         0.2 setosa
## 4          4.6         3.1          1.5         0.2 setosa
## 5          5           3.6          1.4         0.2 setosa
## 6          5.4         3.9          1.7         0.4 setosa
```

Interpretable:

- Categorical features: one-hot/dummy coding
- Continuous features: effect of value being in a certain range
- Other binary features also good! Presence/absence of shapes in image, sequences in text, etc. . .

Fitting a local approximation: general setting

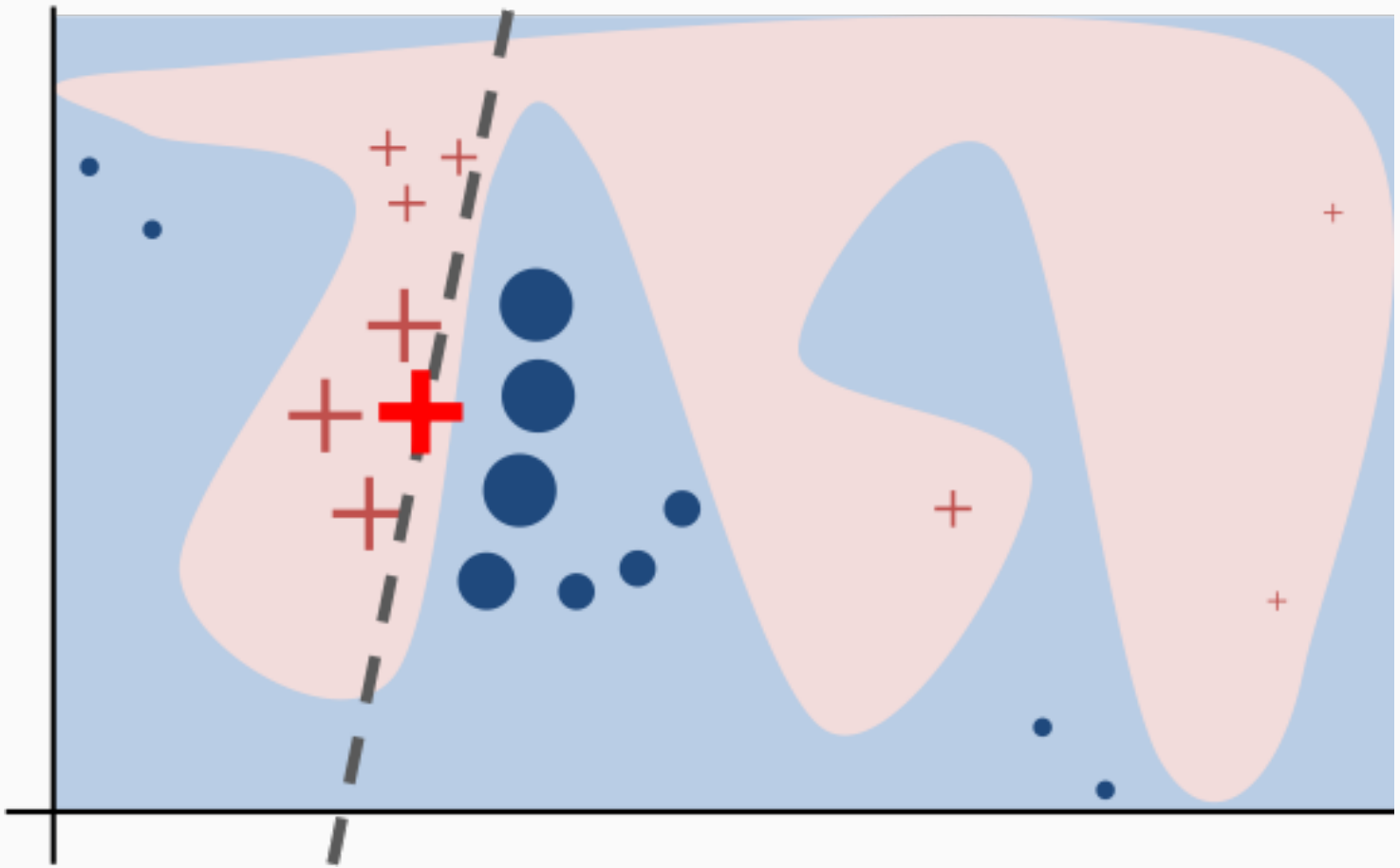
explainer $= \text{argmin}_{g \in G} \, \mathcal{L}(f, g, \pi_x) + \Omega(g)$

- $f(x)$ is the probability that observation x belongs to a particular class given model f
- G is some class of easily understandable models
- $\mathcal{L}(f, g, \pi_x)$ is a loss function
- π_x is a weighting function that gives higher weights to data close to x
- $\Omega(g)$ is some measure of the complexity of g

The `explainer` is an easily understood model where all inputs are binary! It is only locally valid!

The actual estimation process

1. Sample N (typically ~5000) data points from X weighted by π_x



2. Turn these into interpretable data vectors X'
3. Fit an understandable model (i.e. LASSO) on X' with response $f(X)$

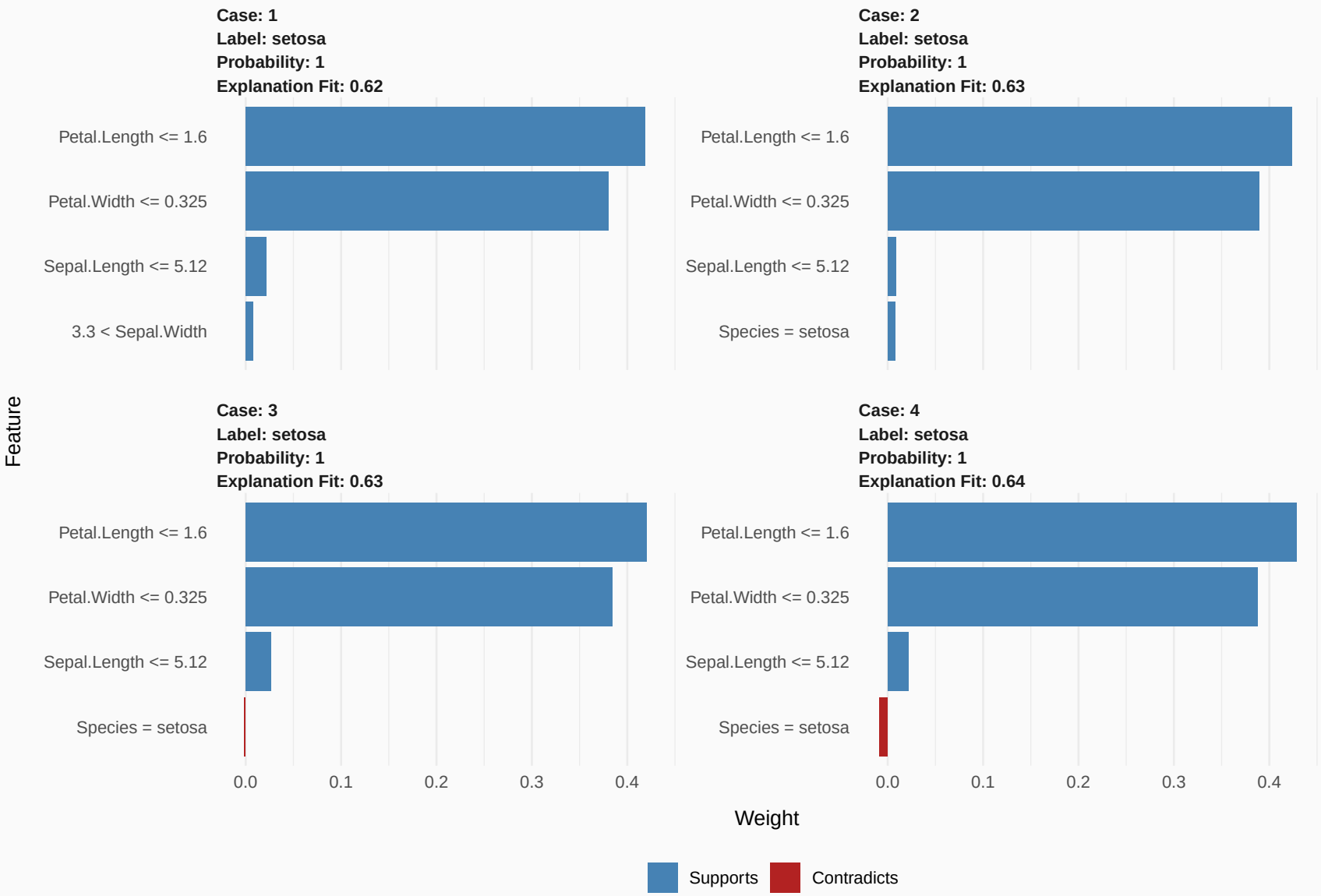
Get to the darn code already

```
library(lime)
library(caret)

 # create train/test sets
iris_train <- slice(iris, 5:n())
iris_test  <- slice(iris, 1:4)

# fit random forest
model <- train(Species ~ ., iris_train,
               method = 'rf')

# fit explainer object
explainer <- lime(iris_train, model)
```

More code

```
# explain observations!
explanation <- explain(iris_test,
                       explainer,
                       n_labels = 1,
                       n_features = 4)

# plot_features(explanation)  -- results on next slide
```

Visual explanations



What is this good for?

- you now have an approximation g of f
- you can understand g

However:

- you have no idea how good the approximation is
- *key*: g **does not** explain what data is causing what response in f

My take: use for diagnostics and intuition only.

- is my model doing something really stupid?
- is there an obvious bias in my model?

`lime` R just works with models from:

- `caret`
- `mlr`
- `xgboost`
- `h2o`
- `keras`

Easy to extend to other packages. Can also explain image and text classifications!

Anything you can send into a neural net and get class probs out of you can explain!

Questions?

The original paper: "Why Should I Trust You?": Explaining the Predictions of Any Classifier

Generalization of LIME: A Unified Approach to Interpreting Model Predictions

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Sparse Linear Explanations

Algorithm 1 Sparse Linear Explanations using LIME

Require: Classifier f, Number of samples N
Require: Instance x, and its interpretable version x'
Require: Similarity kernel π_x, Length of explanation K

$\mathcal{Z} \leftarrow \{\}$
for $i \in \{1, 2, 3, ..., N\}$ **do**
  $z'_i \leftarrow sample\_around(x')$
  $\mathcal{Z} \leftarrow \mathcal{Z} \cup \langle z'_i, f(z_i), \pi_x(z_i) \rangle$
end for
$w \leftarrow$ K-Lasso$(\mathcal{Z}, K)$ ▷ with z'_i as features, $f(z)$ as target
return w

`K-Lasso`: Use RMSE weighted by π_x as loss. Select top K predictors with LASSO. Put these into OLS for final explainer.