

# Methods for Interpretable Machine Learning

PyData - Dec 4, 2018



# About JOOL

ON PURPOSE

ON PURPOSE

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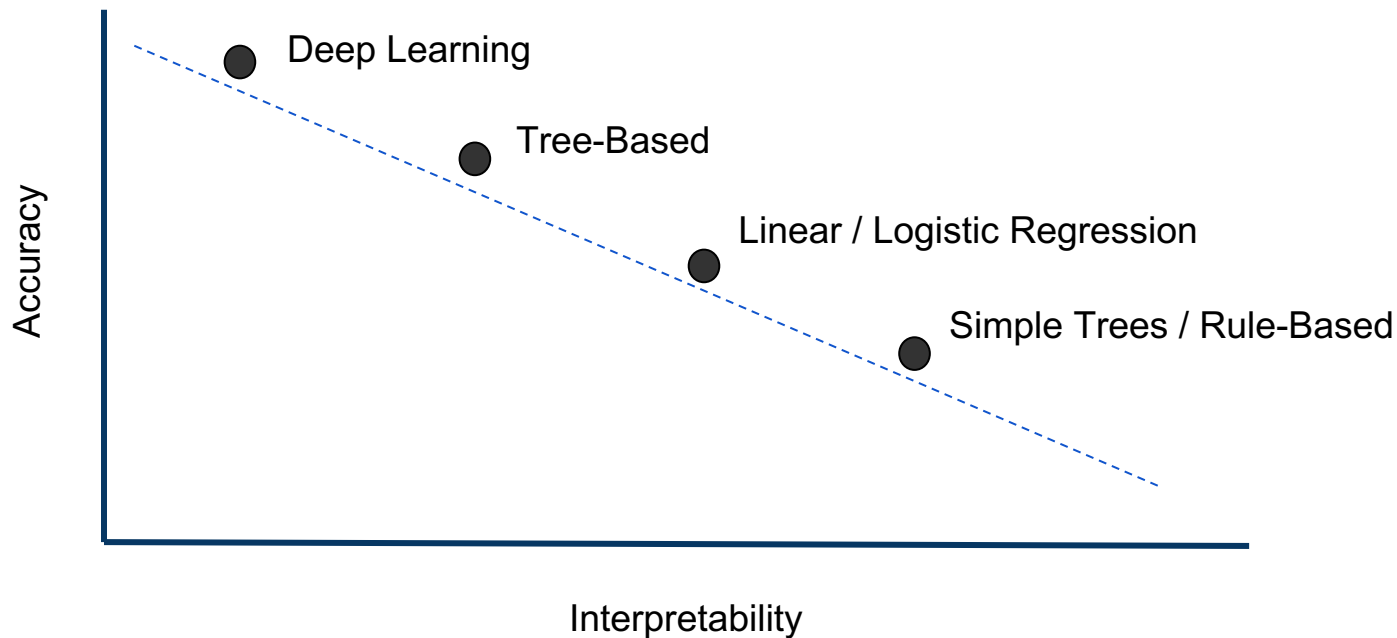
ON PURPOSE

**What do you mean  
“interpretable”...**

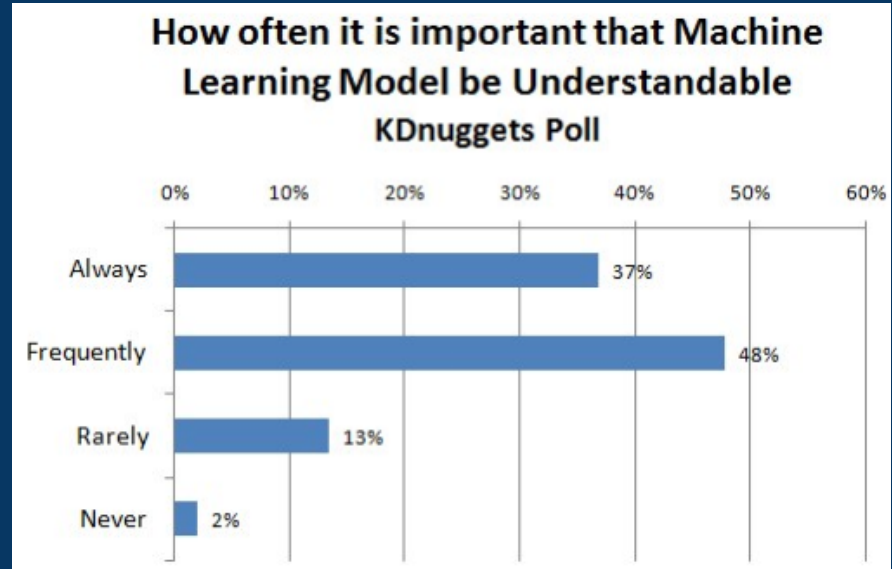


- Human-interpretable?
- Point Estimates, a linear equation?
- Feature Importance?
- Stability / Reproducibility?

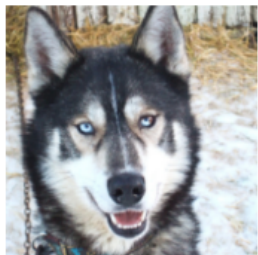
# Accuracy vs. Interpretability Trade-off



# Why do we care?



# Generalization Problems



(a) Husky classified as wolf



(b) Explanation

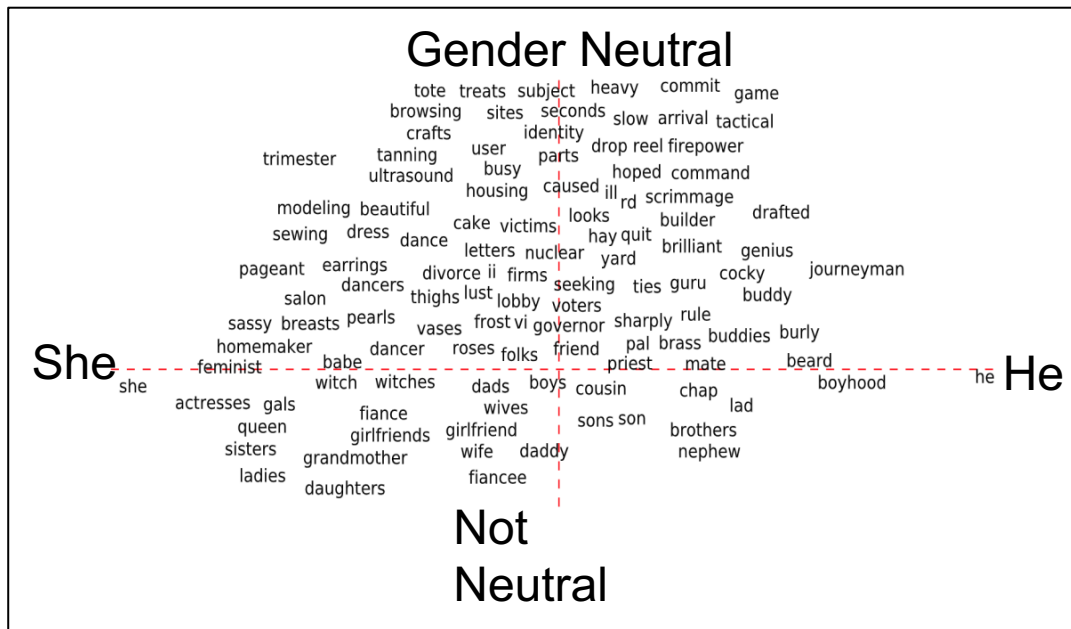
Figure 11: Raw data and explanation of a bad model's prediction in the "Husky vs Wolf" task.

	Before	After
Trusted the bad model	10 out of 27	3 out of 27
Snow as a potential feature	12 out of 27	25 out of 27

Table 2: "Husky vs Wolf" experiment results.

- A model can learn elements from data that aren't core to the problem being solved
  - Over-fitting
  - Spurious correlations (E.g. wolves are more likely to be found in snow than Huskies)

# Models Inherit Bias in the Data



**Amazon scraps secret AI recruiting tool that showed bias against women**



## Machine Bias

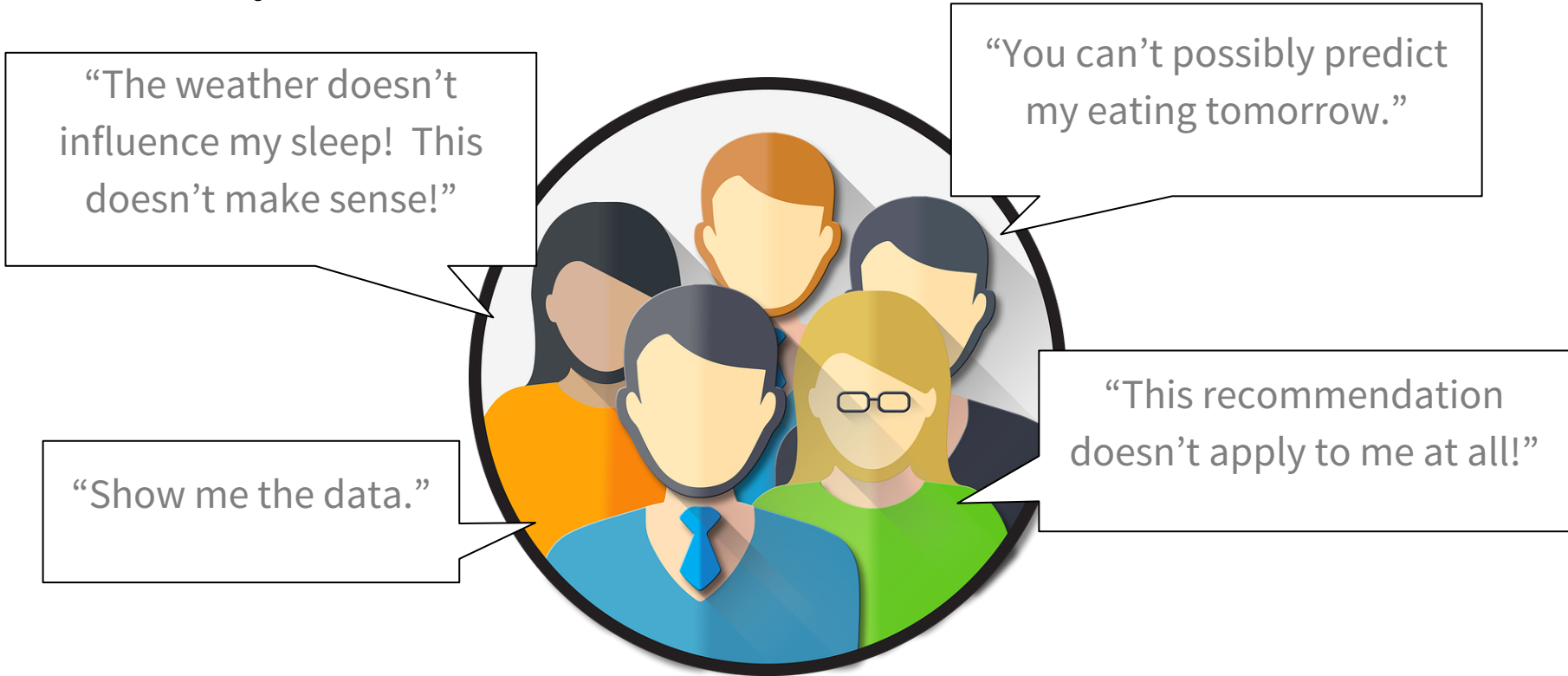
There's software used across the country to predict future criminals. And it's biased against blacks.



# Audit a Model

- Backed by domain knowledge
  - effect size or direction grossly different from expectations
  - latent variables
- Verify safety/limitations
  - local areas of poor accuracy

# User Buy-in



# Regulatory Requirements

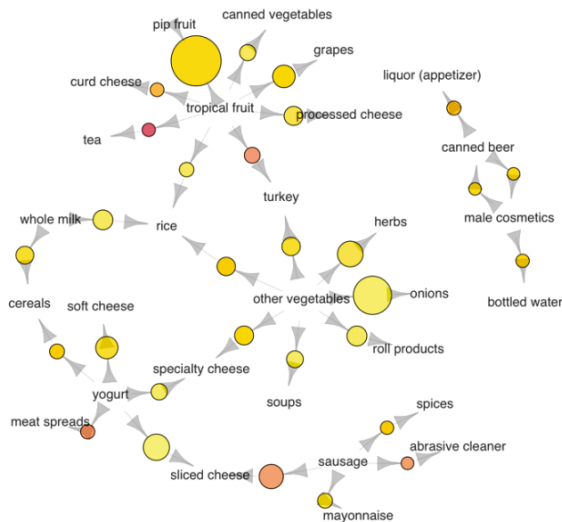
- **Finance:** Fair Credit Reporting Act requires that companies notify a consumer if consumer report information is used to deny credit
- **FDA/Healthcare:** Audit/explain the decision process
- **GDPR:** “Where personal data relating to a data subject are collected from the data subject, the controller shall...provide the data subject with...(f) existence of automated decision-making, including profiling...meaningful information about the logic involved, as well as the significance and the envisaged consequences of such processing for the data subject.” - *Article 13*

**“Perfectly” interpretable  
approaches**

# Rule-based (Assoc. Rules)

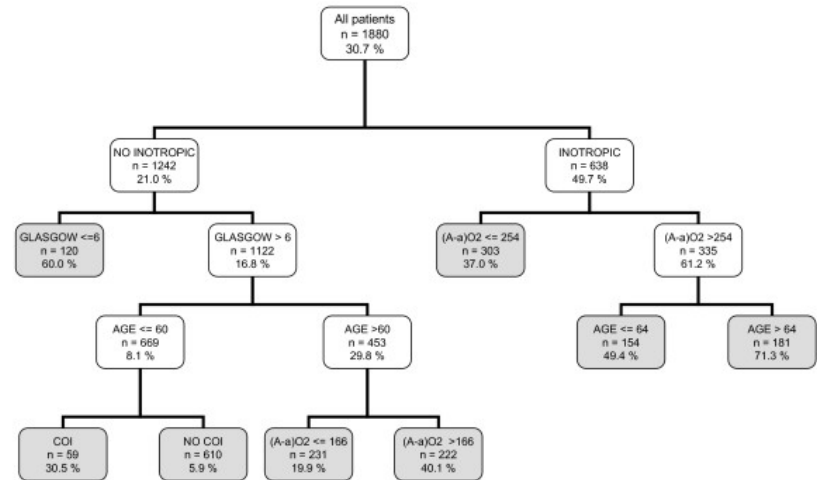
$$\{A, B\} \Rightarrow \{C\}$$

- Apriori, Eclat, FP-Growth
- “If A and B occur, C occurs X% of the time”



# Simple Decision Trees

- Variables have easy to follow split-points that segment outcomes
- Shorter path length is more interpretable



# Linear/Logistic Regression

- Point Estimates
- P-Values
- Odds Ratios

The diagram illustrates the linear regression equation  $Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$  with the following labels and components:

- Dependent Variable:**  $Y_i$
- Population Y intercept:**  $\beta_0$
- Population Slope Coefficient:**  $\beta_1$
- Independent Variable:**  $X_i$
- Random Error term:**  $\varepsilon_i$

The equation is also broken down into two main components using brackets:

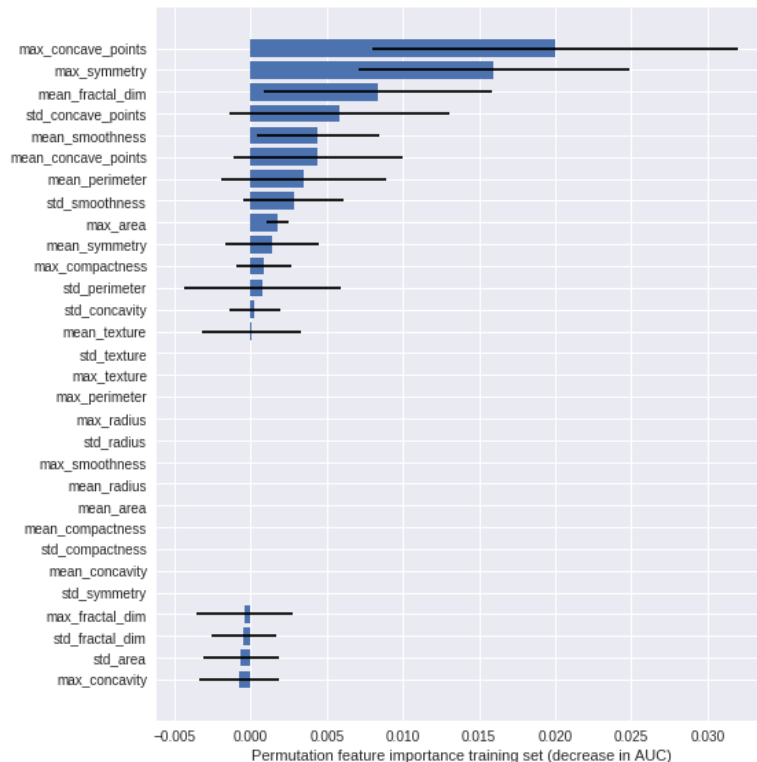
- Linear component:**  $\beta_0 + \beta_1 X_i$
- Random Error component:**  $\varepsilon_i$

# Semi-interpretable approaches



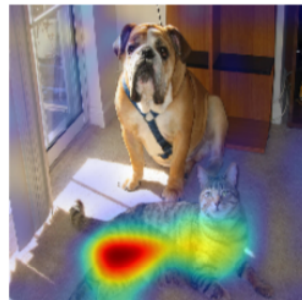
# Variable Importance

- Random Forest, GBM
- Variables are included/excluded in various model iterations
- Measure importance by decrease in accuracy or node purity

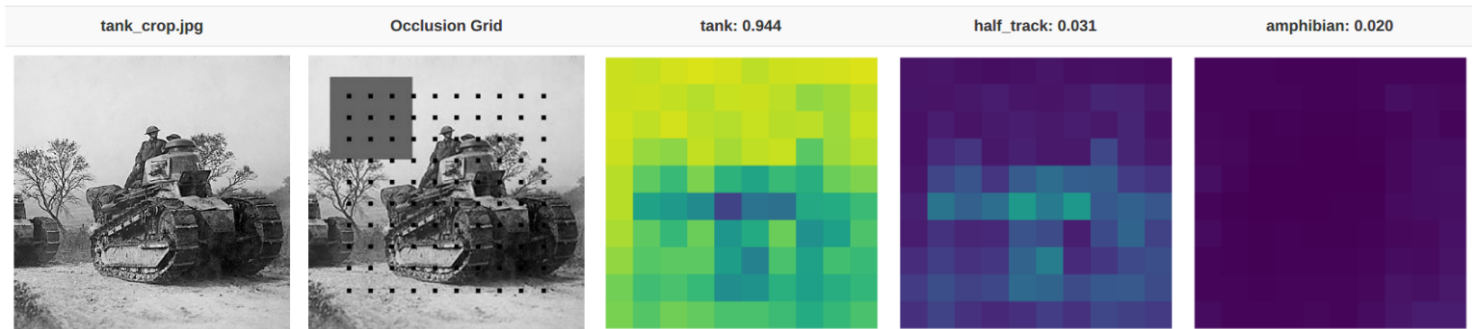


# Neural Network Approaches

- Gradient-Based Methods (Saliency)
  - Partial diff of output w.r.t input
  - Encoder - Decoder Network
  - Use Gradients of last CNN Layer (Grad-CAM)



(c) Grad-CAM 'Cat'



(i) Grad-CAM 'Dog'

# Neural Network Approaches

- Attention Methods (Memory Networks)
  - Visualize Attention Matrix
  - Commonly used with LSTM and CNN architectures

by *ent423* ,*ent261* correspondent updated 9:49 pm et ,thu  
march 19 ,2015 ( *ent261* ) a *ent114* was killed in a parachute  
accident in *ent45* ,*ent85* ,near *ent312* , a *ent119* official told  
*ent261* on wednesday .he was identified thursday as  
special warfare operator 3rd class *ent23* ,29 ,of *ent187* ,  
*ent265* .` *ent23* distinguished himself consistently  
throughout his career .he was the epitome of the quiet  
professional in all facets of his life ,and he leaves an  
inspiring legacy of natural *tenacity* and focused  
...

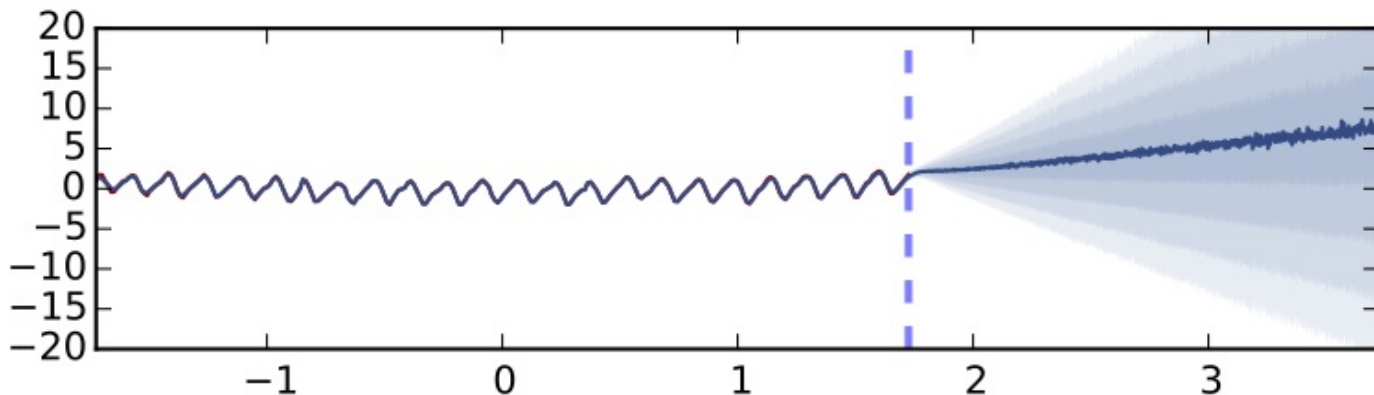
*ent119* identifies deceased sailor as **X** ,who leaves behind  
a wife

by *ent270* ,*ent223* updated 9:35 am et ,mon march 2 ,2015  
( *ent223* ) *ent63* went familial for fall at its fashion show in  
*ent231* on sunday ,dedicating its collection to ``mamma ``  
with nary a pair of ``mom jeans ``in sight .*ent164* and *ent21* ,  
who are behind the *ent196* brand ,sent models down the  
runway in decidedly feminine dresses and skirts adorned  
with roses ,lace and even embroidered doodles by the  
designers ' own nieces and nephews .many of the looks  
featured saccharine needlework phrases like ``i love you ,  
...

**X** dedicated their fall fashion show to moms

# Neural Network Approaches

- Apply Dropout on Inference
  - Requires many additional predictions
  - Returns something similar to a Bayesian Posterior\*



# Neural Network Approaches

- Regularize on the depth of an approximate decision tree
  - Able to produce a decision tree that approximates the complex learned relationships
  - Results in networks that have less complexity given any level of accuracy
  - No work yet on problems with non-interpretable data points (images)



Increased regularization strength

# Model agnostic approaches

# Vary Inputs -> Measure Output

## Pros:

- Works for any model
- X change in input yields an expected Y change in output

## Cons:

- Requires careful planning and understanding of the problem / data
- Requires multiple predictions on same observation
- May want to maintain feature covariance, depending on the model

# Local Interpretable Model-Agnostic Explanations (LIME)

- Vary input data by zeroing out features in the chosen observation
- For images, create “super pixels”
- Weight points by similarity to original
- Fit a simplified linear model on the perturbed observations
- Interpret the linear model



Original Image



Interpretable Components

Prediction probabilities

atheism	0.58
christian	0.42

atheism

Postings  
0.15  
Host  
0.14  
NNTP  
0.11  
edu  
0.04  
have  
0.01  
There  
0.01

christian

## Text with highlighted words

From: johnchad@triton.unm.edu (jchadwic)  
Subject: Another request for Darwin Fish  
Organization: University of New Mexico, Albuquerque  
Lines: 11  
NNTP-Posting-Host: triton.unm.edu

Hello Gang,

There have been some notes recently asking where to obtain the DARWIN fish.  
This is the same question I have and I have not seen an answer on the net. If anyone has a contact please post on the net or email me.



# Takeaways

# Model Interpretability Summary

## Difficult to Interpret

- Neural Networks
- Multi-model ensembles

## Semi-Interpretable

- GBM/XGBoost
- Random Forest
- Large Decision Trees
- Engineered Features

## “Perfectly” Interpretable

- Association Rules
- Simple Decision Trees
- Linear/Logistic Regression

# Good Practices

1. Interpretability can be more important than accuracy
2. Use more interpretable models when possible
3. Keep the audience in mind
4. Consider limitations and biases in the data
5. Several methods exist for interpreting “Black Box” models

# Good Reads

- [The Mythos of Model Interpretability - Zachary Lipton](#)
- [Introduction to LIME](#)
- [What My Deep Learning Model Doesn't Know... - Yarin Gal](#)
- [Teaching Models to Read and Comprehend](#)
- [Beyond Sparsity: Tree Regularization of Deep Models for Interpretability](#)

# Questions?

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