

On the Novel Use of the Welch-Young Inverse Bio-elasticity Coefficient when Building Binary Classification Trees

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Abstract

The use of information gain and gini impurity as split criteria when growing decision trees is shown to be critically-hyper-sub-optimal by extension of the Welch-Takai sampling theorem. A novel split criteria, the Welch-Young Inverse Bio-elasticity Coefficient is introduced and shown to be hyper-optimal by reverse inverse L-norm sampling. Decision tree performance using our novel split criteria is evaluated on a wide range of datasets, showing that we are the fucking shit, and everyone else's shit is bullshit.

1. Introduction

As everyone knows, because it's obvious as shit,¹ misclassification error rate, gini impurity, and information gain are non-optimal criteria for growing decision trees.

- (1) $I(p) = \min(p, 1 - p)$
- (2) $Gini(p) = p(1 - p)$
- (3) $Entropy(p) = p \cdot \log\left(\frac{1}{p}\right) + (1 - p) \cdot \log\left(\frac{1}{1 - p}\right)$

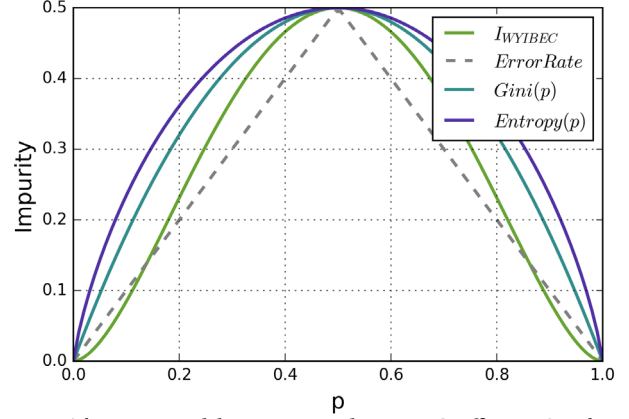


Figure 1. The Young-Welch Inverse Bio-elasticity Coefficient. Our decision tree is class two hyper-optimal, and guarantees performance above the theoretical Welch-Waka-Flocka upper bound.

Below, drawing from information theory, rare bird mating patterns, and quantum sub-particle modeling, we derive the Welch-Young Inverse Bio-elasticity coefficient, a vastly superior split criteria for growing decision trees. Rather than risk insulting the reader by explaining what the fuck is actually going on, we've chosen to just write down a bunch of convoluted equations.

$$\begin{aligned}
 & \frac{D}{Dt} \overline{w^i w'^j} + \overline{w^i w'^z} \nabla_z \bar{u}^j + \overline{w'^j w'^z} \nabla_z \bar{u}^i - \alpha \left(\overline{g^{iz} w'^j} \frac{T'}{\bar{T}} + \overline{g^{jz} w'^i} \frac{T'}{\bar{T}} \right) \left(\nabla_z \Phi + \frac{D\bar{u}_z}{Dt} \right) \\
 & + \frac{1}{\bar{\rho}} \nabla_z [\bar{\rho} \overline{u'^z w'^i w'^j} + (\overline{g^{iz} w'^j} + \overline{g^{jz} w'^i}) P' - \overline{w'^i \sigma^{jz}(u')} - \overline{w'^j \sigma^{iz}(u')}] \\
 & + \frac{1}{\bar{\rho}} \overline{w'^i w'^j \nabla_z (\bar{\rho} u'^z)} - \overline{P' (g^{iz} \nabla_z w'^j + g^{jz} \nabla_z w'^i)} = -\frac{1}{\bar{\rho}} [\overline{\sigma^{iz}(u') \nabla_z w'^j} + \overline{\sigma^{jz}(u') \nabla_z w'^i}] = -\epsilon_2^i, \\
 (1 + e_4) & \frac{D}{Dt} \left(\frac{T'}{\bar{T}} \right)^2 - 2f(t) \left(\frac{T'}{\bar{T}} \right)^2 - 2\overline{w'^z} \frac{T'}{\bar{T}} D_z + \frac{1}{(1 + e_4) \bar{\rho} C_p^2} \nabla_z \left[(1 + e_4)^2 C_p^2 \bar{\rho} \overline{w'^z} \left(\frac{T'}{\bar{T}} \right)^2 \right] + \frac{1 + e_4}{\bar{\rho}} \left(\frac{T'}{\bar{T}} \right)^2 \nabla_z (\rho u'^z) \\
 & + \frac{2}{\bar{\rho} \bar{T} C_p} \frac{T'}{\bar{T}} \left[P' \nabla_z w'^z - \nabla_z (P'_g w'^z) - \frac{D P'_g}{Dt} \right] = \frac{2}{\bar{\rho} \bar{T} C_p} \frac{T'}{\bar{T}} [\overline{\sigma^{z\beta}(u') \nabla_z u'_\beta} - \nabla_z F'_r{}^z] = -\epsilon_2, \\
 (1 + e_4) & \left[\frac{D}{Dt} \left(\overline{w^i} \frac{T'}{\bar{T}} \right) + \overline{w'^z} \frac{T'}{\bar{T}} \nabla_z \bar{u}^i - \alpha \left(\frac{T'}{\bar{T}} \right)^2 g^{iz} \left(\nabla_z \Phi + \frac{D\bar{u}_z}{Dt} \right) \right] - f(t) \overline{w'^i} \frac{T'}{\bar{T}} - \overline{w'^i w'^z} D_z \\
 & + \frac{1}{\bar{\rho} C_p} \nabla_z \left[(1 + e_4) C_p \bar{\rho} \overline{w'^i w'^z} \frac{T'}{\bar{T}} \right] + \frac{1 + e_4}{\bar{\rho}} \overline{w'^i} \frac{T'}{\bar{T}} \nabla_z (\rho u'^z) + \frac{1}{\bar{\rho} \bar{T} C_p} \overline{w'^i} \left[P' \nabla_z w'^z - \nabla_z (P'_g w'^z) - \frac{D P'_g}{Dt} \right] \\
 & = \frac{1 + e_4}{\bar{\rho}} \frac{T'}{\bar{T}} \nabla_z \overline{\sigma^{iz}(u')} + \frac{1}{\bar{\rho} \bar{T} C_p} \overline{w'^i} [\overline{\sigma^{z\beta}(u') \nabla_z u'_\beta} - \nabla_z F'_r{}^z] = -\epsilon_2^i,
 \end{aligned}$$

$$1 = 1$$

$$I_{WYIBEC} = 4 \left(p \cdot \log\left(\frac{1}{p}\right) + (1 - p) \cdot \log\left(\frac{1}{1 - p}\right) \right) p(1 - p)$$