Value-Based Prioritization*

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Abstract

A method is proposed to use value theory to quantitatively prioritize potential actions to accomplish a goal. This method is applied to the example of choosing meaningful work using an example value system based on the desire to reduce suffering.

1 Introduction

Why should a particular goal be pursued ("Why")? Given a goal, what actions should be pursued to best accomplish said goal ("What")? Given an action, how should said action be pursued ("How")?

This article proposes that value theory usually best scopes "Why" and "What" and the scientific method usually best answers "How". A method called Value-Based Prioritization is developed to answer the "What" question:

$$\begin{gathered}\text{Why: } \textit{Value Theory}\\ \downarrow\\ \text{What: } \boldsymbol{\textit{Value-Based Prioritization}}\\ \downarrow\\ \text{How: } \textit{Scientific Method}\end{gathered} \tag{1}$$

2 Why a Goal?

"Why a Goal?" is usually best scoped using value systems because they are evaluative by nature[16]. Evaluating different value systems is left as an (lifelong) exercise for the reader[i].

3 What Actions?

"What Actions?" is usually best scoped by prioritizing actions because actions usually have differing effect sizes and time is limited. It follows from the value system used to answer "Why" that the same value system is used primarily to evaluate the priority of each action.

This article proposes a method called Value-Based Prioritization which builds a quantitative prioritization model based on predicted effect sizes. Raw prioritization scores are further scaled by contextual factors such as implementation time, cost, risk, and other judgments.

4 How to do an Action?

Given answers to "Why?" and "What?", how to implement actions is usually best answered with the scientific method[1]: observations are made and rational thought is used to generate hypotheses, hypotheses are tested with experiments, and successful experiments lead to theories and results.

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*https://github.com/freeradical13/ValueBasedPrioritization

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[i]Example value systems include intuitionism[11], consequentialism[17], evolutionary biology[9], religion[10], epicureanism[13], stoicism[4], political liberalism[19], anarcho-capitalism[12], communitarianism[5], objectivism[3], etc.

5 Value-Based Prioritization

A **value system** V (2) generates a **goal** $G(t)$ (3) (for some future time t) and a set of **mutually exclusive potential future actions** $A(t)$:

$$A(t) = \{A_1(t), \ldots, A_N(t)\},\\ N > 1 \tag{4}$$

An action's **estimated relative accomplishment amount** $B(A(t))$ is an action's expected *relative* (i.e. with respect to other actions) contribution towards accomplishing G(t):

$$B(A(t)) = \mathbb{R},\\ 0 \leq \mathbb{R} \leq 1 \tag{5}$$

Thus, $G(t)$ is fully accomplished if all actions are accomplished:

$$G(t) = \sum_{i=1}^{N} B(A_i(t)) = 1 \tag{6}$$

A **value-based prioritization score** $C(A(t))$ is the result of the product of a set of **value-based prioritization scale functions** $S = \{S_1, \ldots, S_N\}$ (7) multiplied by (5):

$$C(A(t)) = B(A(t)) \cdot \prod_{j=1}^{N} S_j(A(t)),\\ 0 \leq S_j(B(A(t))) \leq 1 \tag{8}$$

Example scale functions include implementation time, cost, risk, and other judgments. Ideally, scale functions should be defined before running the model to reduce bias. The set S always includes the element $S_1(A(t)) = 1$. Note that $\sum_{i=1}^{N} C(A_i(t)) \neq G$ if any $S_j(A_i(t)) < 1$.

A **value-based prioritization** $Z(t)$ is a sequence of actions ordered by prioritization score (8) in descending order:

$$Z(t) = (A_1(t), \ldots, A_N(t)),\\ C(A_1(t)) \geq \ldots \geq C(A_N(t)) \tag{9}$$

The first k actions in $Z(t)$ should be executed in descending priority/proportion where k (10) is chosen based on factors such as available concurrency, time, resources, etc.

6 Modeled Value-Based Prioritization

Historical data may be used to predict actions' estimated relative accomplishment amounts (5) at a future time t_F (11) (e.g. the average time actions will take to ramp up implementation).

If each action has historical data $D(A)$:

$$D(A) =\\ ((t_1, D(A, t_1)), \ldots, (t_N, D(A, t_N))) \tag{12}$$

Then, a set of **comparable prediction models** $R(D(A))$ is applied to each $D(A)$ (e.g. linear regression with different degrees[6]):

$$R(D(A)) =\\ \{R_1(D(A)), \ldots, R_N(D(A))\} \tag{13}$$

The models are compared using **model selection**[20,21] $L(R(D(A)))$ (14) (e.g. adjusted r^2, log-likelihood, AIC[2], BIC[7], etc.).

For each action, the **best fitting model** $M(A(t))$ is selected from $R(D(A))$ using $L(R(D(A)))$.

Each action's $M(A(t_F))$ is used to predict $B(A(t_F))$.

Finally, **modeled value-based prioritization** $Z(t_F)$ (15) is simply (9) with t_F.

7 Choosing Meaningful Work

The following example applies modeled value-based prioritization (15) to the goal of choosing meaningful work. Every aspect is an example and should be reconsidered.

First, outline the parameters:

- (2) V = a value system which answers "Why work?" with "To reduce suffering" which is defined as maximal human suffering: death[ii]. Alternatives include disease burden (e.g. Quality-Adjusted Life Years [QALYs][18]), non-human suffering, pre-birth suffering, etc.
- (3) $G(t)$ = eliminate human death.
- (4) $A(t)$ = the set of actions which would eliminate human death.
- (10) $k = 2$ for a single person, weighted heavily on the first item with the second item being a hedge or volunteer activity.
- (11) t_F = 10 years; an average amount of time under normal conditions to integrate into a new career to work on some subset of $A(t)$ (including learning, certification, building experience, networking, etc.).
- (12) $D(A)$ = time-series data on human death by underlying cause.
- (13) $R(D(A))$ = ordinary least squares linear regression with one, two, three, and four degrees.
- (14) $L(R(D(A)))$ = lowest log-likelihood.

$A(t)$ is the set of 179 actions which would eliminate the 179 major groups (ICD-10 sub-chapters[15]) of underlying causes of death in the United States[8,iii,iv]:

$$\begin{gathered} A(t) = \{ \\ A_1(t) = \text{Eliminate: Malignant neoplasms}, \\ A_2(t) = \text{Eliminate: Ischaemic heart diseases}, \\ \ldots \\ A_{179}(t) = \text{Eliminate: Other disorders of ear} \\ \} \end{gathered}$$

Review the list of actions[v] and hypothesize scale functions. Examples:

- $S_1(A_i) = 1$

  Required scale function.

- $S_2(A_i) = \begin{cases} 0.1 & \text{if } \bar{R}^2 < 0.1 \\ 1 & \text{otherwise} \end{cases}$

  Essentially remove actions with poorly predicted $B(A_i(t_F))$.

- $S_3(A_i) = \begin{cases} 0.1 & \text{if } p(F) > 0.05 \\ 1 & \text{otherwise} \end{cases}$

  Essentially remove actions whose $M(A_i(t))$ p-value of the F-statistic of the fully specified model is not statistically significant. Calculated as the mean squared error of the model divided by the mean squared error of the residuals[vi].

- $S_4(A_i) = \begin{cases} 0.1 & \text{if heteroscedastic} \\ 1 & \text{if homoscedastic} \end{cases}$

  Essentially remove actions with heteroscedastic $M(A_i(t))$: Heteroscedastic if the p-value of the Breusch-Pagan Lagrange Multiplier test is < 0.05[vii].

- $S_5(A_i) = \begin{cases} 0.1 & \text{if no best model} \\ 1 & \text{otherwise} \end{cases}$

  Essentially remove actions which don't have a model that has the lowest log-likelihood.

- $S_6(A_i) = \left(1 - \frac{AverageAge(A_i)}{MaxAge(A(t))}\right)$

  Scale towards younger people as they have more to lose.

- $S_7(A_i) = \left(\frac{(f(A_i) - min(f(A(t)))) \cdot (b-a)}{max(f(A(t)) - min(f(A(t))}\right) + a$

[ii] More accurately, something like the lack of a potential of life.

[iii] Group Results By "Year" And By "ICD Sub-Chapter"; Check "Export Results"; Uncheck "Show Totals"

[iv] `python3 -m vbp.run count_actions UnderlyingCausesOfDeathUnitedStates`

[v] `python3 -m vbp.run list_actions UnderlyingCausesOfDeathUnitedStates`

[vi] https://www.statsmodels.org/dev/generated/statsmodels.regression.linear_model.RegressionResults.html

[vii] https://www.statsmodels.org/dev/generated/statsmodels.stats.diagnostic.het_breuschpagan.html

$f(A_i) = M'(A_i(t_F)), a = 0.5, b = 1$

Scale down by up to half by the relative rate of change of an action's predicted rate of death: Take the derivative of $M(A_i(t))$ and evaluate it with the predicted value and min-max normalize[viii] into $[0.5, 1]$ relative to other actions.

- $S_8(A_i) = \begin{cases} 0.1 & \text{if political/cultural} \\ 1 & \text{otherwise} \end{cases}$

  Essentially remove actions that are primarily political and/or cultural.

The list does not include common scale functions such as implementation time, cost, risk, playing into strengths, piquing interest, market demand, return on investment, ramp-up time, interest, etc. because all medical actions are predicted to be in the same order of magnitude for those scales and all other actions are primarily political so they have a low score, rendering those scales moot.

Create a table listing all actions as rows and all *manually calculated* scale functions as columns[ix,x]:

Action	S_1	...	S_N
A_1	0.1		1
A_2	1		0.25
...			
A_N	0.99		0.9

Table 1: Theoretical scale function table

For example:

Action	S_8
Eliminate: Assault	0.1
Eliminate: Legal intervention ...	0.1
Eliminate: Malnutrition	0.1
Eliminate: Transport accidents	0.1

Table 2: Example scale function table

Outside of the manually calculated scale function table, use obfuscated action names when developing the model to avoid introducing bias.

$D(A)$ for each action is the time-series data of number of deaths per year per 100,000 of population ("Crude Rate")[xi]. For example, for *Malignant neoplasms*[xii]:

Year	Crude Rate
1999	197.0
...	...
2017	183.9

Table 3: Crude rate of deaths per year for *Malignant neoplasms*

Run each comparable prediction model $R_i(D(A))$. For example, see Figure 1 for ordinary least squares linear regressions with polynomial degrees 1, 2, 3, and 4 for *Malignant neoplasms*[xiii].

For each model, calculate the p-value of the F-statistic, $\bar{R}^2$, log-likelihood, and the Breusch-Pagan Lagrange Multiplier test. Filter out models whose p-value of the F-statistic is > 0.05 or p-value of Breusch-Pagan is < 0.05 and choose the model that has the lowest log-likelihood. If no models are found, perform the same procedure independent of

[viii] https://en.wikipedia.org/wiki/Normalization_(statistics)

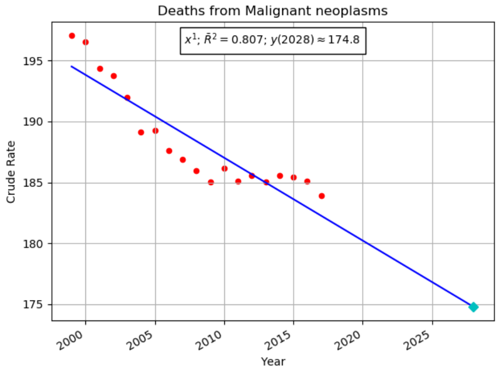
[ix] For the example scale functions, this is only $S_7(A_i)$.

[x] `python3 -m vbp.run scale_functions -t excel -o scale_functions.xslx -n "Scale Values" -p "Eliminate: " UnderlyingCausesOfDeathUnitedStates S7`

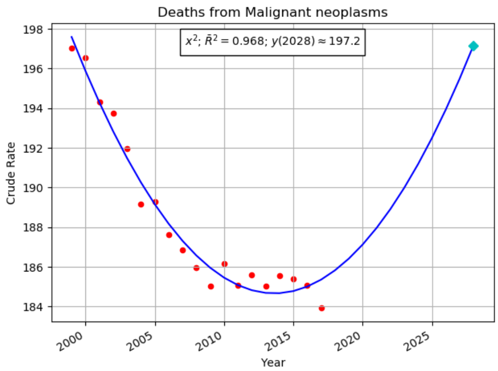
[xi] https://wonder.cdc.gov/wonder/help/cmf.html#Frequently%20Asked%20Questions%20about%20Death%20Rates

[xii] `python3 -m vbp.run action_data UnderlyingCausesOfDeathUnitedStates "Malignant neoplasms"`

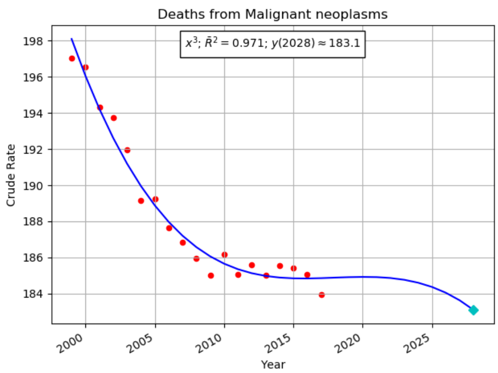
[xiii] `python3 -m vbp.run predict UnderlyingCausesOfDeathUnitedStates "Malignant neoplasms" -d -m 1 -x 4 --do-not-obfuscate -p 10`



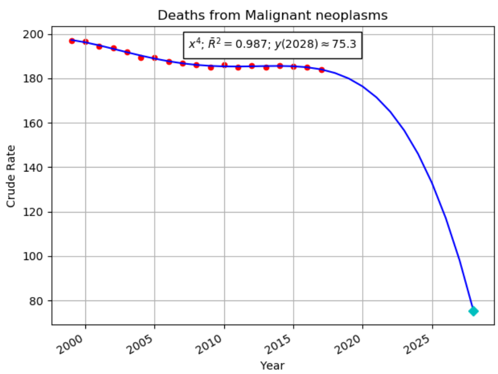
(a) 1 degree



(b) 2 degrees



(c) 3 degrees



(d) 4 degrees

Figure 1: Ordinary least squares linear regression with polynomial degrees 1, 2, 3, and 4 for *Malignant neoplasms*

the p-value tests (the scale functions $S_2(A_i)$ and $S_3(A_i)$ will scale down the chosen model later). If no models are found, choose the degree-1 regression based on the assumption that most disease trends do not tend to change in higher-order ways.

For each model, calculate the predicted value for t_F (setting negative values to 0).

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