

Value-Based Prioritization

Kevin Grigorenko

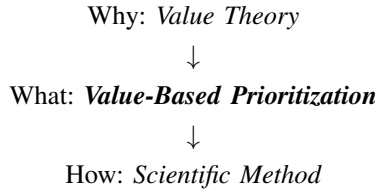
Abstract

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.

I. INTRODUCTION

Why should a particular goal be pursued (“Why”)? Given a goal, what actions should be pursued to best accomplish that goal (“What”)? Given an action, how should that 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:



II. WHY A GOAL?

“Why a Goal?” is usually best scoped using value systems because they are evaluative by nature³⁴. Comparing value systems is left as an (lifelong) exercise for the readerⁱ.

III. 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.

<https://github.com/freeradical13/ValueBasedPrioritization>
kevin@myplaceonline.com

ⁱExample value systems include intuitionism¹⁶, consequentialism³⁵, evolutionary biology¹³, religion¹⁵, epicureanism²², stoicism⁴, political liberalism⁴¹, anarcho-capitalism¹⁸, communitarianism⁵, objectivism³, etc.

IV. HOW TO DO AN ACTION?

Given answers to “Why?” and “What?”, how to implement actions is usually best answered with the scientific method^{1,26}: observations are made and rational thought is used to generate hypotheses, hypotheses are tested with experiments, and successful experiments lead to theories and results.

V. VALUE-BASED PRIORITIZATION

A **value system** V (1) generates a **goal** $G(t)$ (2) (for some future time t) and a set of **mutually exclusive potential future actions** $A(t)$:

$$A(t) = \{A_1(t), \dots, A_N(t)\}, \quad (3)$$

$$N > 1$$

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 $G(t)$:

$$B(A(t)) = \mathbb{R}, \quad (4)$$

$$0 \leq \mathbb{R} \leq 1$$

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

$$G(t) = \sum_{i=1}^N B(A_i(t)) = 1 \quad (5)$$

A **value-based prioritization score** $C(A(t))$ is the result of the product of a set of **value-based prioritization scale functions** $S = \{S_1, \dots, S_N\}$ (6) multiplied by (4):

$$C(A(t)) = B(A(t)) \cdot \prod_{j=1}^N S_j(A(t)), \quad (7)$$

$$0 \leq S_j(A(t)) \leq 1$$

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 (7) in descending order:

$$\begin{aligned} Z(t) &= (A_1(t), \dots, A_N(t)), \\ C(A_1(t)) &\geq \dots \geq C(A_N(t)) \end{aligned} \quad (8)$$

The first k actions in $Z(t)$ should be executed in descending priority/proportion where k (9) is chosen based on factors such as available concurrency, time, resources, etc.

VI. MODELED VALUE-BASED PRIORITIZATION

Historical data may be used to predict actions' estimated relative accomplishment amounts (4) at a future time t_F (10).

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

$$D(A) = ((t_1, D(A, t_1)), \dots, (t_N, D(A, t_N))) \quad (11)$$

Then, a set of **comparable prediction models** (or forecasting models)^{12,20,36,37,42} $R(D(A))$ is applied to each $D(A)$ (e.g. exponential smoothing^{19,20,ii}, a generalized additive model [GAM]³⁷, ARIMA^{20,iii}, linear regression^{20,iv}, machine learning²⁵, seasonal algorithms such as TBATS^{20,v}, poisson log-bilinear regression²⁸, etc.):

$$R(D(A)) = \{R_1(D(A)), \dots, R_N(D(A))\} \quad (12)$$

The models are compared using a **model selection** algorithm^{vi} $L(R(D(A)))$ (13) (e.g. smallest Akaike's Information Criterion [AIC], smallest Corrected AIC [AICc], smallest Bayesian Information Criterion [BIC], smallest cross-validation, largest adjusted coefficient of determination [\bar{R}^2], etc.).

For each action, $L(R(D(A)))$ produces the **best fitting model** $M(A(t))$ (or a model that's an average of multiple models^{11,vii}).

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

Finally, **modeled value-based prioritization** $Z(t_F)$ (14) is simply (8) with t_F .

VII. CHOOSING MEANINGFUL WORK

The following example applies modeled value-based prioritization (14) to the goal of choosing meaningful work²⁷. Every aspect is an example and should be reconsidered.

First, outline the parameters:

- (1) V = a value system which answers “Why work?” with “To reduce suffering” which is defined as maximal human suffering: death^{viii}. Alternatives include morbidity and disease burden (e.g. Quality-Adjusted Life Years [QALYs]^{23,40}), non-human suffering, cost effectiveness^{14,21,29}, economic impact³³, existential risks⁶, pre-birth suffering, working to give²⁴, etc.
- (2) $G(t)$ = eliminate human death.
- (3) $A(t)$ = the set of actions which would eliminate human death.
- (9) $k = 1$ for a single person (or 2 to hedge the failure of the first action or to add a volunteer activity).
- (10) $t_F = 10$ 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.).
- (11) $D(A)$ = time-series data on human death by underlying cause^{ix}.
- (12) $R(D(A))$ = exponential smoothing functions using Holt's linear trend method as aggregate models^{x,xi,xii,xiii}.

$$\{ETS(A, A, N), ETS(A, A_d, N)\},$$

$$\phi = 0.98$$

Commonly used alternative models in all-cause mortality forecasting include poisson log-bilinear regressions:

“There is a substantial literature on the projection or forecasting of all-cause mortality rates and mortality rates for specific diseases. The methods used fall into two broad groups. First are those methods based on time-series analysis of historical trends in mortality rates. These ‘aggregate models,’ whether for all-cause mortality or for specific causes, use the previous trend of the variable of interest as the basis for predicting its future value. By their data requirements, such methods are generally limited to high-income countries with good death registration data [...]. Second are the ‘structural models,’ which are based on relationships between mortality and a set of independent variables, and are necessarily projections of those independent variables. To the extent that the structural model identifies the important components — and the relationships among them — of the ‘system’ that determines the variable of interest, they offer the potential for more robust predictions. When the underlying system is complex and sensitive to one or more of its components, a

^{viii}More accurately, something like the lack of a potential of life.

^{ix}<https://www.who.int/topics/mortality/en/>

^x<https://otexts.com/fpp2/holt.html>

^{xi}<https://otexts.com/fpp2/ets.html>

^{xii}https://www.statsmodels.org/dev/examples/notebooks/generated/exponential_smoothing.html

^{xiii} $ETS(A, M, N)$ and $ETS(A, M_d, N)$ were tested but had bad failure modes, particularly with outliers.

ⁱⁱ<https://otexts.com/fpp2/expsmooth.html>

ⁱⁱⁱ<https://otexts.com/fpp2/arima.html>

^{iv}<https://otexts.com/fpp2/regression.html>

^v<https://otexts.com/fpp2/advanced.html>

^{vi}<https://otexts.com/fpp2/selecting-predictors.html>

^{vii}<https://otexts.com/fpp2/combinations.html>

shift in some of the system variables can introduce large changes in the outcome that may be missed by extrapolation (such as the discovery of antibiotics and infectious disease trends or the change in tuberculosis mortality after the HIV epidemic). Aggregate models, in contrast, require considerably less knowledge of the system components and the relationships among them. These models can therefore provide more reliable estimates when such information is not available, especially when the system is not very sensitive to its inputs in time intervals that are in the order of the prediction time.”²⁸

- (13) $L(R(D(A)))$ = lowest AICc.

$A(t)$ is a set of actions which would eliminate the groups of Underlying Causes of Death (UCOD) as classified by the International Classification of Diseases (ICD)^{30,31,32,xiv}.

This example starts by looking at the longterm comparable leading causes of death for the United States^{7,9,10,38,39,xvxi}:

$$A(t) = \{ \\ A_1(t) = \text{Eliminate: Heart disease,} \\ A_2(t) = \text{Eliminate: Cancer,} \\ \dots \\ \}$$

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

- $S_1(A_i) = 1$

Required scale function.

- $S_2(A_i) = \left(1 - \frac{\text{AverageAge}(A_i(t_{max-5:t_{max}}))}{\text{MaxAge}(A(t))}\right)$

Scale towards younger people because they have more to lose: one minus the ratio of the average age³⁸ over the last 5 years compared to the maximum age of all deaths.

- $S_3(A_i) = \left(\frac{(f(A_i) - \min(f(A(t)))) \cdot (b-a)}{\max(f(A(t)) - \min(f(A(t))))}\right) + a$,

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

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 into $[0.5, 1]$ relative to other actions.

- $S_4(A_i) = \begin{cases} 0.1 & \text{if political/cultural} \\ 1 & \text{otherwise} \end{cases}$

Essentially remove actions that are primarily political and/or cultural¹⁷.

^{xiv}For a discussion of chapters, sub-chapters, and codes, see pages 13-17 of ICD-10 Volume 2³⁰. For a discussion of the definition of underlying cause of death, see page 31 of ICD-10 Volume 2³⁰.

^{xv}`python3 -m vbp.run list UCODUnitedStates`

^{xvi}See Appendix note 1 on how the data was generated.

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 they are either considered irrelevant^{xvii} or moot after applying S_4 .

Create a table listing all actions as rows and all manually calculated scale functions as columns^{xviii,xix}:

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

TABLE I: Theoretical manually calculated scale function table

For example, see Table II:

Action (Eliminate: ...)	S_4
Homicide	0.1

TABLE II: Example manually calculated scale function table for the longterm comparable leading causes of death for the United States

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 some number of population (the “Crude Rate”^{xx}; 100,000 for the U.S. and 1,000,000 for the world). For example, for *Cancer*^{xxi}, see Table III:

Year	Crude Rate
1900	61.612658
1901	63.969191
...	...
2016	185.319100
2017	184.217584

TABLE III: Crude rate of deaths per year for *Cancer* for the Longterm comparable leading causes of death for the United States

Run each comparable prediction model $R_i(D(A))$. For example, for *Cancer*^{xxii}, see Figure 1:

^{xvii}The irrelevance of some common scale functions rests on the privilege of having the flexibility to pursue options independent of immediate primal concerns.

^{xviii}For the longterm comparable leading causes of death for the United States, this is only $S_4(A_i)$.

^{xix}`python3 -m vbp.run manual_scale_functions -a -t excel -o manual_scale_functions.xlsx -n "Scale Values" -p "Eliminate: " UCODUnitedStates S4`

^{xx}<https://wonder.cdc.gov/wonder/help/cmf.html#Frequently%20Asked%20Questions%20about%20Death%20Rates>

^{xxi}`python3 -m vbp.run action_data UCODUnitedStates Cancer`

^{xxii}`python3 -m vbp.run predict UCODUnitedStates --ets-no-multiplicative-models --do-not-obfuscate -p 10 Cancer`

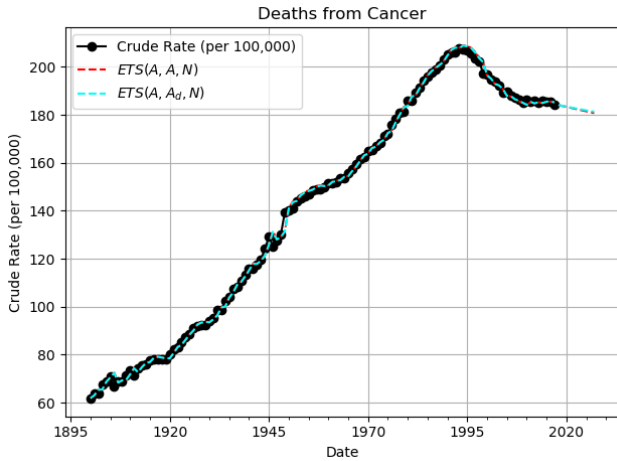


Fig. 1: Exponential smoothing functions $ETS(A, A^*, N)$, $\phi = 0.98$ using Holt’s linear trend method for *Cancer* for the Longterm comparable leading causes of death for the United States

Scedasticity, forecast uncertainty, and cross-validation are not considered because it’s not clear how to automate processing of such data to tune or choose models.

For each model, calculate AICc and choose the model $M(A(t_F))$ that has the lowest AICc. For example, see Table IV:

$R_i(D(A))$	AICc	Predicted
$ETS(A, A, N)$	128.37	180.73
$ETS(A, A_d, N)$	128.83	181.29

TABLE IV: Example AICc values of $R_i(D(A))$ for *Cancer* for the Longterm comparable leading causes of death for the United States

Use each $M(A(t_F))$ ’s predicted value (setting negative values to 0) and generate all of the relative $B(t_F)$ values along with any scale functions based on the models (e.g. scaling by the relative prediction derivatives using S_3). For example, see Table V:

Action	$B(t_F)$	S_1	S_3
Name02	0.305	1	0.682
Name18	0.281	1	0.634
...

TABLE V: Example $B(t_F)$ values and model-based scale function values for the Longterm comparable leading causes of death for the United States

Combine the table above with the manually calculated scale functions table I and any other calculated scale functions (e.g. $S_2(A_i)$) to create the final table with all scale function values. For example, see Table VI:

Action	$B(t_F)$	S_1	S_2	S_3	S_4
Name02	0.305	1	0.386	0.682	1
Name18	0.281	1	0.435	0.634	1
...

TABLE VI: Example $B(t_F)$ values with all scale function values for the Longterm comparable leading causes of death for the United States

Calculate the product of each action’s $B(t_F)$ and its scale function values to produce the final $Z(t_F)$ table and then sort by the values in descending order and choose the top k actions.

For the longterm comparable leading causes of death for the United States, the results^{xxiii} are in Table VII and Figure 2:

k	Action (Eliminate: ...)	$Z(t_F)$
1	Name02	0.080375
2	Name18	0.077476
3	Name25	0.034373
4	Name21	0.025423
5	Name26	0.014776

TABLE VII: $Z(t_F)$ table for the Longterm comparable leading causes of death for the United States

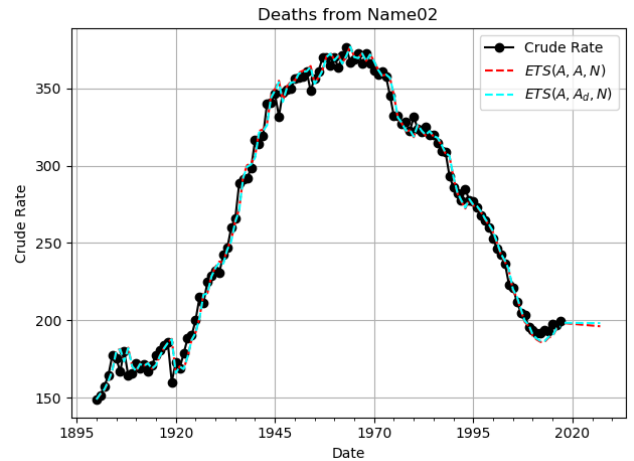


Fig. 2: Highest priority action from the Longterm comparable leading causes of death for the United States: *Name02*

The same analysis is run on other mutually exclusive groupings of causes of death^{xxiv}:

^{xxiii}`python3 -m vbp.run modeled_value_based_prioritization UCODUnitedStates --ets-no-multiplicative-models -k 5 -p 10 --manual-scales manual_scale_functions.xlsx --average-ages S2 --average-age-range 5`
^{xxiv}Prefix the data source with the `-a` flag to run for all data types; for example: `python3 -m vbp.run modeled_value_based_prioritization -a UCODUnitedStates ...`

- 1) ICD-9 and ICD-10 113 Cause List for the United States^{2,7,8,38,xxv,xxvi,xxvii} in Table IX and Figure 4:

k	Action (Eliminate: ...)	$Z(t_F)$
1	Name046	0.032929
2	Name058	0.025236
3	Name010	0.022342
4	Name029	0.015068
5	Name092	0.013543

TABLE VIII: $Z(t_F)$ table for the ICD-9 and ICD-10 113 Cause List for the United States

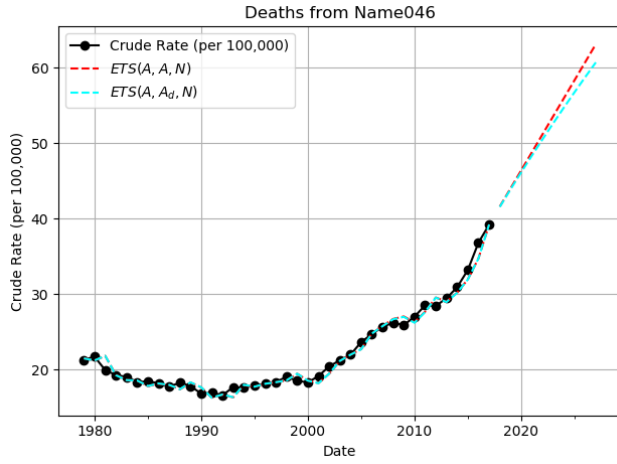


Fig. 3: Highest priority action from the ICD-9 and ICD-10 113 Cause List for the United States: *Name046*

- 2) ICD-9 and ICD-10 113 Cause List for the United States, including subtotals in Table IX and Figure 4:

k	Action (Eliminate: ...)	$Z(t_F)$
1	Name117	0.049639
2	Name009	0.031924
3	Name030	0.021617
4	Name030	0.019517
5	Name073	0.019465

TABLE IX: $Z(t_F)$ table for the ICD-9 and ICD-10 113 Cause List for the United States, including subtotals

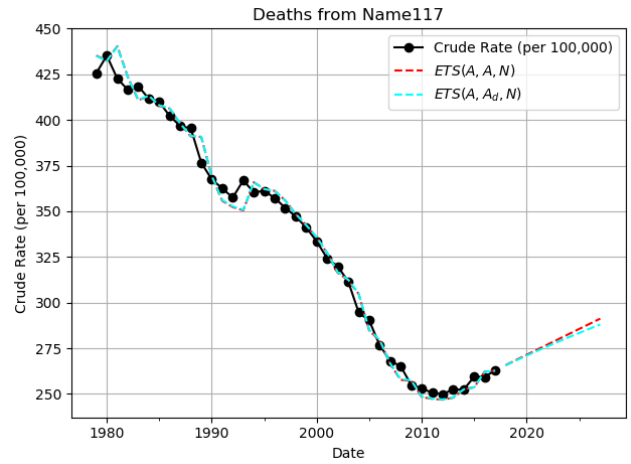


Fig. 4: Highest priority action from the ICD-9 and ICD-10 113 Cause List for the United States, including subtotals: *Name117*

^{xxv} ftp://ftp.cdc.gov/pub/Health_Statistics/NCHS/Datasets/Comparability/icd9_icd10/Comparability_Ratio_tables.xls

^{xxvi} <https://wonder.cdc.gov/wonder/help/ucd.html#ICD-10%20113%20Cause%20List>

^{xxvii} https://www.cdc.gov/nchs/data/dvs/Multiple_Cause_Record_Layout_2016.pdf, page 19; The list actually has 118 mutually exclusive groups instead of 113.

- 3) ICD-9 and ICD-10 113 Cause List for the United States with only top-level groupings in Table X and Figure 5:

k	Action (Eliminate: ...)	$Z(t_F)$
1	Name117	0.131121
2	Name126	0.050850
3	Name073	0.045513
4	Name091	0.017207
5	Name050	0.012517

TABLE X: $Z(t_F)$ table for the ICD-9 and ICD-10 113 Cause List for the United States with only top-level groupings

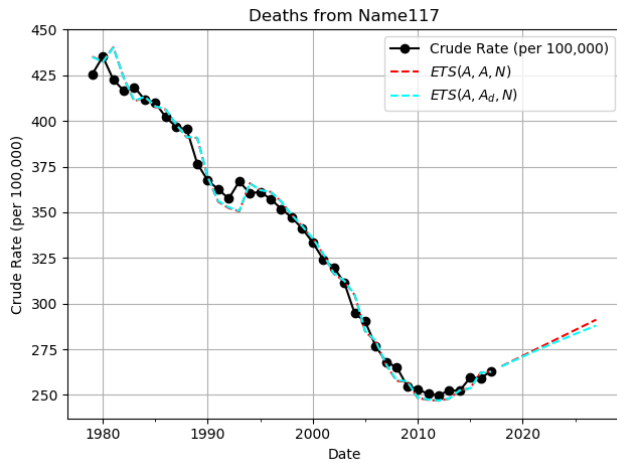


Fig. 5: Highest priority action from the ICD-9 and ICD-10 113 Cause List for the United States with only top-level groupings: *Name117*

- 4) ICD-10 Chapters for the United States^{7,xxviii} in Table XI and Figure 6:

k	Action (Eliminate: ...)	$Z(t_F)$
1	Name16	0.101677
2	Name17	0.060121
3	Name14	0.039507
4	Name01	0.037175
5	Name18	0.026494

TABLE XI: $Z(t_F)$ table for the ICD-10 Chapters for the United States

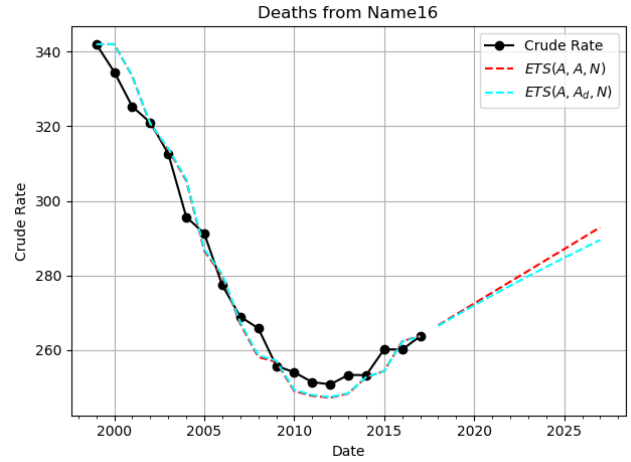


Fig. 6: Highest priority action from the ICD-10 Chapters for the United States: *Name16*

^{xxviii}Group Results By “Year” And By “ICD Chapter”; Check “Export Results”; Uncheck “Show Totals”

- 5) ICD-10 Sub-Chapters for the United States^{7,xxix} in Table XII and Figure 7:

k	Action (Eliminate: ...)	$Z(t_F)$
1	Name093	0.060440
2	Name026	0.038374
3	Name101	0.037231
4	Name037	0.027645
5	Name075	0.025999

TABLE XII: $Z(t_F)$ table for the ICD-10 Sub-Chapters for the United States

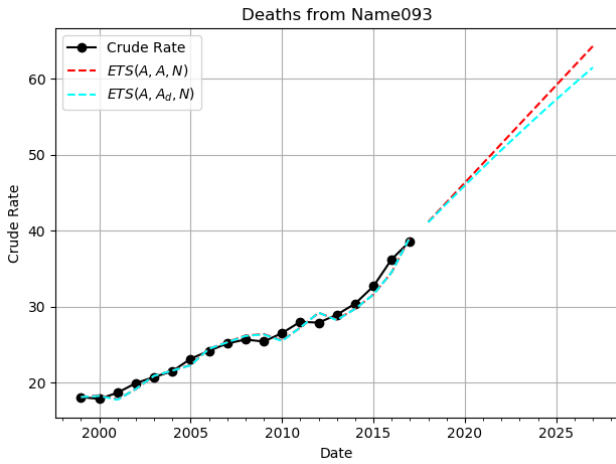


Fig. 7: Highest priority action from the ICD-10 Sub-Chapters for the United States: *Name093*

- 6) Minimally grouped (5,264) causes of death for the United States^{7,xxx,xxxi} in Table XIII and Figure 8:

k	Action (Eliminate: ...)	$Z(t_F)$
1	Name0856	0.013730
2	Name4563	0.012711
3	Name2111	0.012563
4	Name0653	0.011704
5	Name3874	0.007563

TABLE XIII: $Z(t_F)$ table for the Minimally grouped (5,264) causes of death for the United States

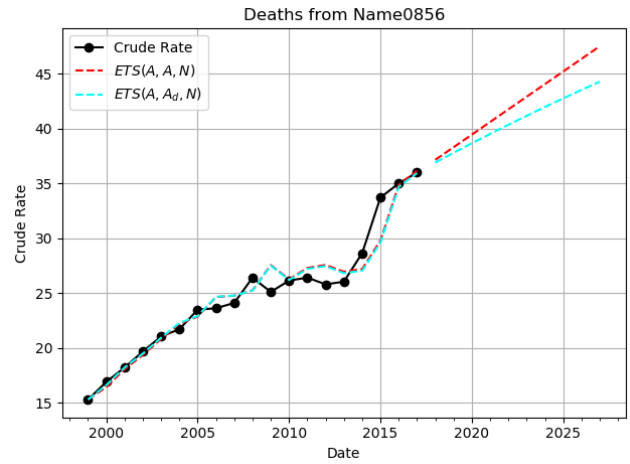


Fig. 8: Highest priority action from the Minimally grouped (5,264) causes of death for the United States: *Name0856*

^{xxix}Group Results By “Year” And By “ICD Sub-Chapter”; Check “Export Results”; Uncheck “Show Totals”

^{xxx}Group Results By “Year” And By “Cause of death”; Check “Export Results”; Uncheck “Show Totals”

^{xxxi}Without S_4 due to the sheer number of causes.

- 7) Minimally grouped (11,316) causes of death for the World^{43xxxii,xxxiii,xxxiv} in Table XIV and Figure 9:

k	Action (Eliminate: ...)	$Z(t_F)$
1	Name01002	0.026866
2	Name04954	0.024561
3	Name05025	0.022585
4	Name06345	0.019871
5	Name01748	0.018749

TABLE XIV: $Z(t_F)$ table for the Minimally grouped (11,316) causes of death for the World

- 8) ICD-10 Chapters for the World, including subtotals^{43,xxxv} in Table XV and Figure 10:

k	Action (Eliminate: ...)	$Z(t_F)$
1	Name038	0.160800
2	Name216	0.097424
3	Name059	0.092250
4	Name151	0.046399
5	Name148	0.034819

TABLE XV: $Z(t_F)$ table for the ICD-10 Chapters for the World, including subtotals

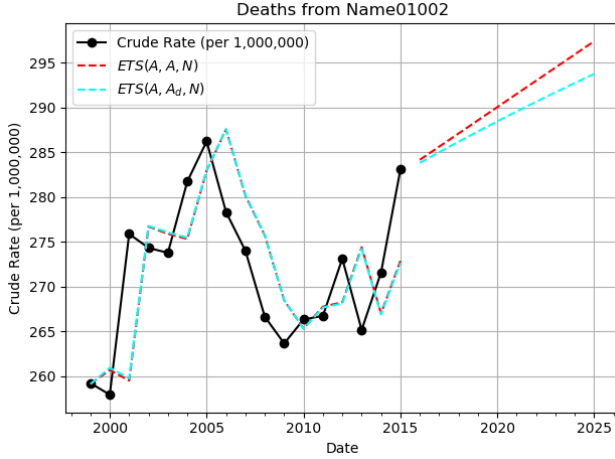


Fig. 9: Highest priority action from the Minimally grouped (11,316) causes of death for the World: *Name01002*

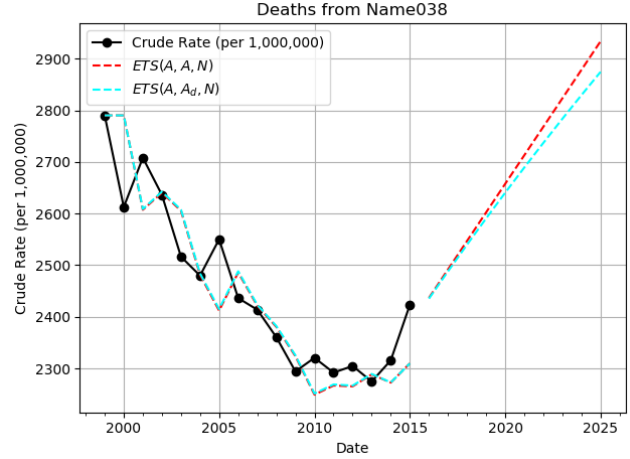


Fig. 10: Highest priority action from the ICD-10 Chapters for the World, including subtotals: *Name038*

^{xxxii}`python3 -m vbp.run modeled_value_based_prioritization`
`UCODWorld --ets-no-multiplicative-models -k 5 -p`
`10 --manual-scales manual_scale_functions.xlsx`
^{xxxiii}Without S_3 because comprehensive granular age data doesn't exist.
^{xxxiv}Without S_4 due to the sheer number of causes.

^{xxxv}See footnote ^{xxxiii}.

- 9) ICD-10 Chapters for the World with only top-level groupings^{43,xxxvi} in Table XVI and Figure 11:

k	Action (Eliminate: ...)	$Z(t_F)$
1	Name038	0.321104
2	Name216	0.194456
3	Name151	0.092581
4	Name129	0.043816
5	Name055	0.032951

TABLE XVI: $Z(t_F)$ table for the ICD-10 Chapters for the World with only top-level groupings

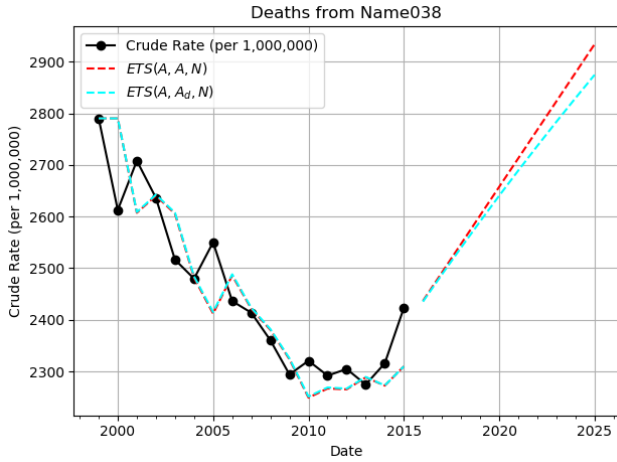


Fig. 11: Highest priority action from the ICD-10 Chapters for the World with only top-level groupings: *Name038*

- 10) ICD-10 Sub-Chapters for the World^{43,xxxvii} in Table XVII and Figure 12:

k	Action (Eliminate: ...)	$Z(t_F)$
1	Name059	0.216971
2	Name148	0.076670
3	Name197	0.038095
4	Name189	0.032015
5	Name092	0.031105

TABLE XVII: $Z(t_F)$ table for the ICD-10 Sub-Chapters for the World

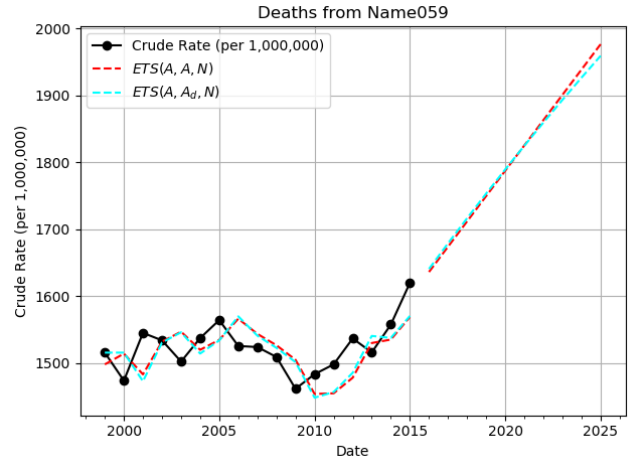


Fig. 12: Highest priority action from the ICD-10 Sub-Chapters for the World: *Name059*

VIII. DISCUSSION

TODO

^{xxxvi}See footnote ^{xxxiii}.

^{xxxvii}See footnote ^{xxxiii}.

REFERENCES

- [1] Hanne Andersen and Brian Hepburn. Scientific method. In Edward N. Zalta, editor, *The Stanford Encyclopedia of Philosophy*. Metaphysics Research Lab, Stanford University, summer 2016 edition, 2016. <https://plato.stanford.edu/archives/sum2016/entries/scientific-method/>.
- [2] Robert N Anderson, Arialdi M Miniño, Donna L Hoyert, and Harry M Rosenberg. Comparability of cause of death between icd-9 and icd-10: Preliminary estimates. 2001. https://www.cdc.gov/nchs/data/nvsr/nvsr49/nvsr49_02.pdf.
- [3] Neera K. Badhwar and Roderick T. Long. Ayn rand. In Edward N. Zalta, editor, *The Stanford Encyclopedia of Philosophy*. Metaphysics Research Lab, Stanford University, fall 2017 edition, 2017. <https://plato.stanford.edu/archives/fall2017/entries/ayn-rand/>.
- [4] Dirk Baltzly. Stoicism. In Edward N. Zalta, editor, *The Stanford Encyclopedia of Philosophy*. Metaphysics Research Lab, Stanford University, summer 2018 edition, 2018. <https://plato.stanford.edu/archives/sum2018/entries/stoicism/>.
- [5] Daniel Bell. Communitarianism. In Edward N. Zalta, editor, *The Stanford Encyclopedia of Philosophy*. Metaphysics Research Lab, Stanford University, summer 2016 edition, 2016. <https://plato.stanford.edu/archives/sum2016/entries/communitarianism/>.
- [6] Nick Bostrom. Existential risk prevention as global priority. *Global Policy*, 4(1):15–31, 2013. <http://www.existential-risk.org/concept.pdf>.
- [7] Centers for Disease Control and Prevention and National Center for Health Statistics. Underlying Cause of Death 1999-2017 on CDC WONDER Online Database, released December, 2018. Data are from the Multiple Cause of Death Files, 1999-2017, as compiled from data provided by the 57 vital statistics jurisdictions through the Vital Statistics Cooperative Program. <https://wonder.cdc.gov/ucd-icd10.html>. Accessed: 2019-03-01.
- [8] Centers for Disease Control and Prevention and National Center for Health Statistics. A Guide to State Implementation of ICD-10 for Mortality; Part II: Applying Comparability Ratios. <https://www.cdc.gov/nchs/data/statab/document-for-the-states.pdf>. Accessed: 2019-03-01.
- [9] Centers for Disease Control and Prevention and National Center for Health Statistics. United States Population by Age, Race, and Sex, 1900-90, and 1991-2001. https://www.cdc.gov/nchs/nvss/mortality/historical_population.htm. Accessed: 2019-03-01.
- [10] Centers for Disease Control and Prevention and National Center for Health Statistics. Leading Causes of Death, 1900-1998. https://www.cdc.gov/nchs/nvss/mortality_historical_data.htm. Accessed: 2019-03-01.
- [11] Robert T Clemen. Combining forecasts: A review and annotated bibliography. *International journal of forecasting*, 5(4):559–583, 1989. <https://faculty.fuqua.duke.edu/~clemen/bio/Published%20Papers/13.CombiningReview-Clemen-IJOF-89.pdf>.
- [12] Jan G De Gooijer and Rob J Hyndman. 25 years of time series forecasting. *International journal of forecasting*, 22(3):443–473, 2006. [http://www.est.uc3m.es/esp/nueva_docencia/comp_col_get/lade/tecnicas_prediccion/Practicas0708/Practical1/25%20years%20of%20time%20series%20forecasting%20\(Gooijer%20and%20Hyndman\).pdf](http://www.est.uc3m.es/esp/nueva_docencia/comp_col_get/lade/tecnicas_prediccion/Practicas0708/Practical1/25%20years%20of%20time%20series%20forecasting%20(Gooijer%20and%20Hyndman).pdf).
- [13] William FitzPatrick. Morality and evolutionary biology. In Edward N. Zalta, editor, *The Stanford Encyclopedia of Philosophy*. Metaphysics Research Lab, Stanford University, spring 2016 edition, 2016. <https://plato.stanford.edu/archives/spr2016/entries/morality-biology/>.
- [14] GiveWell.org. Some considerations against more investment in cost-effectiveness estimates. <https://blog.givewell.org/2011/11/04/some-considerations-against-more-investment-in-cost-effectiveness-estimates/>. Accessed: 2019-03-01.
- [15] John Hare. Religion and morality. In Edward N. Zalta, editor, *The Stanford Encyclopedia of Philosophy*. Metaphysics Research Lab, Stanford University, winter 2014 edition, 2014. <https://plato.stanford.edu/archives/win2014/entries/religion-morality/>.
- [16] Michael Huemer. *Ethical Intuitionism*. Springer, 2007. <https://spot.colorado.edu/~huemer/5.htm>.
- [17] Michael Huemer. In praise of passivity. *Studia Humana*, 1(2):12–28, 2012. <http://atavisionary.com/wp-content/uploads/2017/08/In-Praise-of-Passivity.pdf>.
- [18] Michael Huemer. *The Problem of Political Authority*. Springer, 2013. <https://spot.colorado.edu/~huemer/1.htm>.
- [19] Rob Hyndman, Anne B Koehler, J Keith Ord, and Ralph D Snyder. *Forecasting with exponential smoothing: the state space approach*. Springer Science & Business Media, 2008. <http://www.exponentialsMOOTHING.net/>.
- [20] Rob J Hyndman and George Athanasopoulos. *Forecasting: principles and practice*. OTexts, 2018. <https://otexts.com/fpp2/>.
- [21] Dean T Jamison, Hellen Gelband, Susan Horton, Prabhat Jha, Ramanan Laxminarayan, Charles N Mock, and Rachel Nugent. *Disease Control Priorities, (Volume 9): Improving Health and Reducing Poverty*. The World Bank, 2017. <https://openknowledge.worldbank.org/bitstream/handle/10986/28877/9781464805271.pdf>.
- [22] David Konstan. Epicurus. In Edward N. Zalta, editor, *The Stanford Encyclopedia of Philosophy*.

- Metaphysics Research Lab, Stanford University, summer 2018 edition, 2018. <https://plato.stanford.edu/archives/sum2018/entries/epicurus/>.
- [23] Alan D Lopez, Colin D Mathers, Majid Ezzati, Dean T Jamison, and Christopher JL Murray. *Global burden of disease and risk factors*. The World Bank, 2006. <https://openknowledge.worldbank.org/bitstream/handle/10986/7039/364010PAPE R0G1101OFFICIAL0USE0ONLY1.pdf>.
- [24] William MacAskill. *Doing good better: Effective altruism and a radical new way to make a difference*. Guardian Faber Publishing, 2015.
- [25] Spyros Makridakis, Evangelos Spiliotis, and Vassilios Assimakopoulos. The m4 competition: Results, findings, conclusion and way forward. *International Journal of Forecasting*, 34(4): 802–808, 2018. https://www.researchgate.net/profile/Spyros_Makridakis/publication/325901666_The_M4_Competition_Results_findings_conclusion_and_way_forward/links/5b2c9aa4aca2720785d66b5e/The-M4-Competition-Results-findings-conclusion-and-way-forward.pdf.
- [26] Peter Markie. Rationalism vs. empiricism. In Edward N. Zalta, editor, *The Stanford Encyclopedia of Philosophy*. Metaphysics Research Lab, Stanford University, fall 2017 edition, 2017. <https://plato.stanford.edu/archives/fall2017/entries/rationalism-empiricism/>.
- [27] Frank Martela and Michael F Steger. The three meanings of meaning in life: Distinguishing coherence, purpose, and significance. *The Journal of Positive Psychology*, 11(5):531–545, 2016. <https://www.ippanetwork.org/wp-content/uploads/2017/02/Martela-Steger-JOPP.pdf>.
- [28] Colin D Mathers and Dejan Loncar. Projections of global mortality and burden of disease from 2002 to 2030. *PLoS medicine*, 3(11):e442, 2006. <https://journals.plos.org/plosmedicine/article/file?id=10.1371/journal.pmed.0030442&type=printable>.
- [29] Peter J Neumann, Jordan E Anderson, Ari D Panzer, Elle F Pope, Brittany N D’Cruz, David D Kim, and Joshua T Cohen. Comparing the cost-per-qalys gained and cost-per-dalys averted literatures. *Gates open research*, 2, 2018. https://dpo52087pnd5x.cloudfront.net/manuscripts/13870/5db9cb3d-9e5e-456b-9276-52dc2973b97b_12786_-_Peter_Neumann_V2.pdf.
- [30] World Health Organization. *International statistical classification of diseases and related health problems*, volume 2. World Health Organization, 10th edition, 2010. https://www.who.int/classifications/icd/ICD10Volume2_en_2010.pdf.
- [31] World Health Organization. *International statistical classification of diseases and related health problems*, volume 1. World Health Organization, 10th edition, 2016. <https://apps.who.int/iris/bitstream/handle/10665/246208/9789241549165-V1-eng.pdf>.
- [32] World Health Organization. *International statistical classification of diseases and related health problems*, volume 3. World Health Organization, 10th edition, 2016. <https://apps.who.int/iris/bitstream/handle/10665/246208/9789241549165-V3-eng.pdf>.
- [33] World Health Organization et al. WHO guide to identifying the economic consequences of disease and injury. 2009. https://www.who.int/choice/publications/d_economic_impact_guide.pdf.
- [34] Mark Schroeder. Value theory. In Edward N. Zalta, editor, *The Stanford Encyclopedia of Philosophy*. Metaphysics Research Lab, Stanford University, fall 2016 edition, 2016. <https://plato.stanford.edu/archives/fall2016/entries/value-theory/>.
- [35] Walter Sinnott-Armstrong. Consequentialism. In Edward N. Zalta, editor, *The Stanford Encyclopedia of Philosophy*. Metaphysics Research Lab, Stanford University, winter 2015 edition, 2015. <https://plato.stanford.edu/archives/win2015/entries/consequentialism/>.
- [36] Leonard J Tashman and Michael L Leach. Automatic forecasting software: A survey and evaluation, 1991. https://www.researchgate.net/profile/Len_Tashman/publication/223444048_Automatic_forecasting_software_A_survey_and_evaluation/links/5ad7af42aca272fdaf8029b3/Automatic-forecasting-software-A-survey-and-evaluation.pdf.
- [37] Sean J Taylor and Benjamin Letham. Forecasting at scale. *The American Statistician*, 72(1):37–45, 2018. <https://peerj.com/preprints/3190.pdf>.
- [38] The National Bureau of Economic Research. Mortality Data: Vital Statistics NCHS’ Multiple Cause of Death Data, 1959-2017. <https://www.nber.org/data/vital-statistics-mortality-data-multiple-cause-of-death.html>. Accessed: 2019-03-01.
- [39] U.S. Census Bureau. Historical National Population Estimates. <https://www2.census.gov/programs-surveys/popest/tables/1900-1980/national/totals/popclockest.txt>. Accessed: 2019-03-01.
- [40] Milton C Weinstein, George Torrance, and Alistair McGuire. QALYs: the basics. *Value in health*, 12: S5–S9, 2009. <https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1524-4733.2009.00515.x>.
- [41] Leif Wenar. John rawls. In Edward N. Zalta, editor, *The Stanford Encyclopedia of Philosophy*. Metaphysics Research Lab, Stanford University, spring 2017 edition, 2017. <https://plato.stanford.edu/archives/spr2017/entries/rawls/>.
- [42] Ernst Wit, Edwin van den Heuvel, and Jan-Willem Romeijn. ‘all models are wrong...’: an introduction to model uncertainty. *Statistica Neerlandica*, 66 (3):217–236, 2012. <https://www.rug.nl/research/portals/files/13270992/2012StatistNeerlWit.pdf>.

- [43] World Health Organization. WHO Mortality Database. https://www.who.int/healthinfo/statistics/mortality_rawdata/en/. Accessed: 2019-03-01.

IX. APPENDIX

Notes on Section VII:

- 1) To generate the longterm comparable leading causes of death for the United States:
 - a) Generate data from 1959 for all long-term, comparable, leading causes of death^{xxxviii}:

```
python3 -m vbp.run
prepare_data UCODUnitedStates
```
 - b) Rows 1900:1957 and the sheet “Comparability Ratios” in comparable_ucod_estimates.xlsx were manually input from https://www.cdc.gov/nchs/data/dvs/lead1900_98.pdf.
 - c) Open comparable_data_since_1959.xlsx and copy rows 1959:Present.
 - d) Open comparable_ucod_estimates.xlsx and paste on top starting at 1959.
 - e) Process comparable_ucod_estimates.xlsx with its “Comparability Ratios” sheet to generate comparable_ucod_estimates_ratios_applied.xlsx:

```
python3 -m vbp.run
prepare_data UCODUnitedStates
--comparable-ratios
```
- 2) Age adjustment^{xxxix} is not performed on crude rates because the goal of the example is to predict future *relative* total death rates which already implicitly takes into account population age changes over time.
- 3) The WHO Mortality Database population and death statistics are quite incomplete, reporting only about $\frac{1}{3}$ of the world population and about $\frac{1}{3}$ of world deaths:

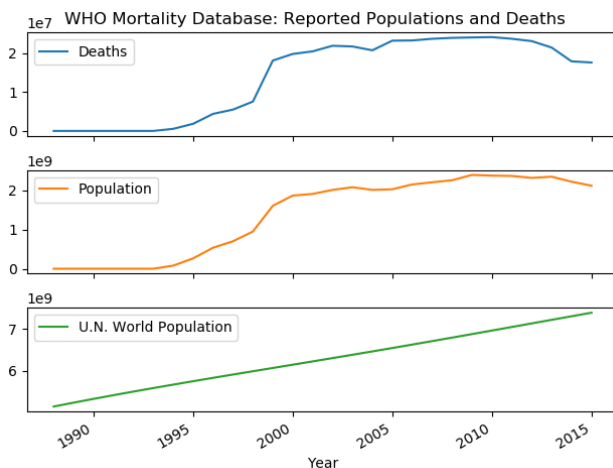


Fig. 13: WHO Mortality Database: Reported Population and Deaths

- 4) “Substantial research remains to develop robust and unbiased methods for measuring trends in case

fatality rates, survival times, and disability due to specific causes, let alone collecting such data across all regions of the world. Despite these uncertainties, projections provide a useful perspective on population health trends and health policies, provided that they are interpreted with a degree of caution. Projections enable us to appreciate better the implications for health and health policy of currently observed trends, and the likely impact of fairly certain future trends, such as the ageing of the population, and the continuation of the epidemiological transition in developing countries.”²⁸

- 5) “The process of coding underlying causes of death involves some extent of misattribution or miscoding even in countries where causes are assigned by medically qualified staff [due to] incorrect or systematic biases in diagnosis, incorrect or incomplete death certificates, misinterpretation of ICD rules for selection of the underlying cause, and variations in the use of coding categories for unknown and ill-defined causes.”^{xl}

^{xxxviii} https://www.cdc.gov/nchs/data/dvs/lead1900_98.pdf

^{xxxix} <https://seer.cancer.gov/seerstat/tutorials/aarates/definition.html>

^{xl} <https://apps.who.int/healthinfo/statistics/mortality/whodpms/help/desc.htm>