Value-Based Prioritization: A method for choosing meaningful work*

Kevin Grigorenko†

April 16, 2019

Abstract

A method is proposed to use value theory to select and quantitatively prioritize actions to accomplish a goal. Actions are relatively ranked based on some quantitative measurement(s) as called for by the value theory. This ranking is transformed by a set of functions which scale up and down each action's relative score based on other relevant measurements and subjective opinions. The resulting list provides a prioritized relative ranking of actions that should be pursued in a particular order. This method is applied to the example of choosing meaningful work using an example value system based on the goal to reduce human suffering.

1. Background

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")?

1.1. Existing research

To exemplify these questions, the issue of choosing meaningful work is selected. One field that investigates the question of meaningful work is psychology, largely in specialties such as positive and vocational psychology.

Although there are significant efforts to establish the importance of a meaningful life [1–7] and meaningful work [8–11], calling [12], or purpose [13], and survey perceptions of meaningful work [14], efforts to provide detailed methods of choosing such meaningful work are largely confined to vague techniques such as evaluations of psychological profiles for signature strengths [15], career counseling [9] or therapy [16], and job search training [17]. These approaches are important prerequisites but their less quantitative and less explicit nature make them difficult to evaluate, generalize, and improve.

2. Value-Based Prioritization

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:

Why: *Value Theory*

↓

What: *Value-Based Prioritization*

↓

How: *Scientific Method*

2.1. Why a Goal?

"Why a Goal?" is usually best scoped using value systems because they are evaluative by nature [18]. Comparing value systems is left as an (lifelong) exercise for the reader[i].

2.2. 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.

Value-Based Prioritization 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.

2.3. How to do an Action?

Given answers to "Why?" and "What?", how to implement actions is usually best answered with the scientific method [29,30]: observations are made and rational thought is used to generate hypotheses, hypotheses are tested with experiments, and successful experiments lead to theories and results.

2.4. Method

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

$$A(t) = \{A_1(t), \ldots, A_N(t)\}, \quad N > 1 \tag{3}$$

An action's *estimated relative accomplishment*

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

† kevin@myplaceonline.com

[i] Example value systems include intuitionism [19], consequentialism [20], evolutionary biology [21], religion [22], epicureanism [23], stoicism [24], political liberalism [25], anarcho-capitalism [26], communitarianism [27], objectivism [28], etc.

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

$$B(A(t)) = \mathbb{R}, \quad 0 \leq \mathbb{R} \leq 1 \tag{4}$$

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

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

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

$$C(A(t)) = B(A(t)) \cdot \prod_{j=1}^{N} S_j(A(t)), \quad 0 \leq S_j(A(t)) \leq 1 \tag{7}$$

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 $S_1(A(t)) = 1$.

A *value-based prioritization* $Z(t)$ is a sequence of actions ordered by prioritization score (7) in descending order:

$$Z(t) = (A_1(t), \ldots, A_N(t)), \quad C(A_1(t)) \geq \ldots \geq C(A_N(t)) \tag{8}$$

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.

2.5. 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 $D(A)$:

$$D(A) = ((t_1, D(A, t_1)), \ldots, (t_N, D(A, t_N))) \tag{11}$$

Then, a set of *comparable prediction models* (or forecasting models)[31–35] $R(D(A))$ is applied to each $D(A)$ (e.g. exponential smoothing[33,36,ii], a generalized additive model [GAM][34], ARIMA[33,iii], linear regression[33,iv], machine learning[37], seasonal algorithms such as TBATS[33,v], poisson log-bilinear regression[38], etc.):

$$R(D(A)) = \{R_1(D(A)), \ldots, R_N(D(A))\} \tag{12}$$

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[39,vii]).

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

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

$$Z(t_F) = (A_1(t_F), \ldots, A_N(t_F)), \quad C(A_1(t_F)) \geq \ldots \geq C(A_N(t_F)) \tag{14}$$

3. Choosing Meaningful Work

The following example applies modeled value-based prioritization (14) to the goal of choosing meaningful work. 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 human suffering" which is defined as maximal human suffering: death (more precisely, something like the lack of a potential of life). Alternatives include morbidity and disease burden (e.g. Quality-Adjusted Life Years [QALYs][40,41]), non-human suffering, cost effectiveness[42–44], economic impact[45], existential risks[46], pre-birth suffering, working to give[47], 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[viii].
- (12) $R(D(A))$ = exponential smoothing functions using Holt's linear trend method as aggregate models[ix,x,xi] ($ETS(A,M,N)$ and $ETS(A,M_d,N)$ were tested but had bad failure modes, particularly with outliers.):

  $$\{ETS(A,A,N), ETS(A,A_d,N)\}, \quad \phi = 0.98$$

  Commonly used alternative models in all-cause mortality forecasting include poisson log-bilinear regressions[xii].
- (13) $L(R(D(A)))$ = lowest AICc.

[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
[viii] https://www.who.int/topics/mortality/en/
[ix] https://otexts.com/fpp2/holt.html
[x] https://otexts.com/fpp2/ets.html
[xi] https://www.statsmodels.org/dev/examples/notebooks/generated/exponential_smoothing.html
[xii] See Appendix note 4.

$A(t)$ 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)[48–50,xiii].

This example starts by looking at the longterm comparable leading causes of death for the United States[51–55,xiv,xv]:

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

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

- $S_1(A_i) = 1$

  Required scale function.

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

  Scale towards younger people because they have more to lose: one minus the ratio of the average age[52] 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 cultural[56].

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[xvi] or moot after applying S_4. The inverse of existing market investment might be interesting to consider.

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

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

Table 1: Theoretical manually calculated scale function table

For example, see Table 2:

Action (Eliminate: ...)	S_4
Homicide	0.1

Table 2: 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"[xix]; 100,000 for the U.S. and 1,000,000 for the world). For example, for *Cancer*[xx], see Table 3:

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

Table 3: 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*[xxi], see Figure 1:

[xiii] For a discussion of chapters, sub-chapters, and codes, see pages 13-17 of ICD-10 Volume 2[49]. For a discussion of the definition of underlying cause of death, see page 31 of ICD-10 Volume 2[49].

[xiv] See Appendix command 1.

[xv] See Appendix note 1 on how the data was generated.

[xvi] The irrelevance of some common scale functions rests on the privilege of having the flexibility to pursue options independent of immediate primal concerns.

[xvii] For the longterm comparable leading causes of death for the United States, this is only $S_4(A_i)$.

[xviii] See Appendix command 2.

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

[xx] See Appendix command 3.

[xxi] See Appendix command 4.

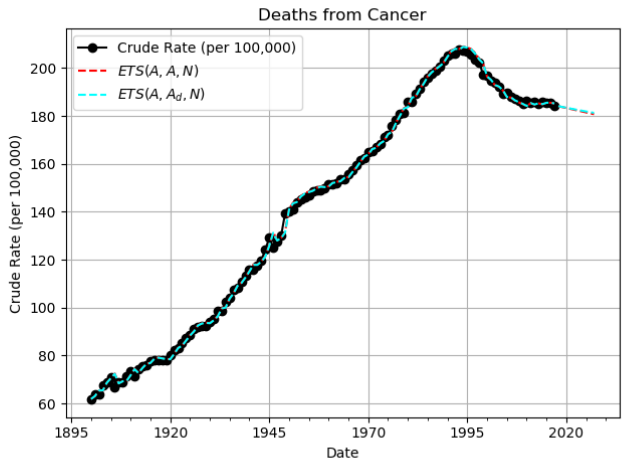

Figure 1: Exponential smoothing functions $ETS(A,A*,N), \phi = 0.98$ using Holt's linear trend method for *Cancer* for the Longterm comparable leading causes of death for the United States

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 4:

$R_i(D(A))$	AICc	Predicted
$\boldsymbol{ETS(A,A,N)}$	**128.37**	**180.73**
$ETS(A,A_d,N)$	128.83	181.29

Table 4: 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 5:

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

Table 5: 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 (Table 1) 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 6:

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 6: 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.

3.1. Results

For the longterm comparable leading causes of death for the United States, the results[xxii] are in Table 7 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 7: $Z(t_F)$ table for the Longterm comparable leading causes of death for the United States

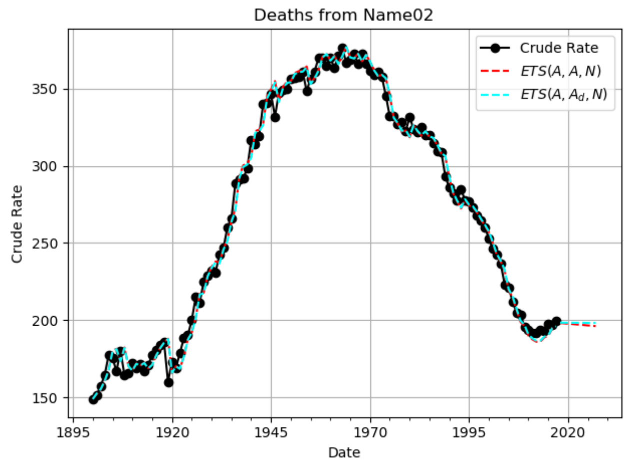

Figure 2: Highest priority action from the Longterm comparable leading causes of death for the United States: *Name02*

The same analysis is run on other mutually exclusive groupings of causes of death[xxiii]:

1. ICD-9 and ICD-10 113 Cause List for the United States[52,53,57,58,xxiv,xxv,xxvi] in Table 9 and Figure 4:

[xxii] See Appendix command 5.
[xxiii] Prefix the data source with the `-a` flag to run for all data types; for example, see Appendix command 6.
[xxiv] ftp://ftp.cdc.gov/pub/Health_Statistics/NCHS/Datasets/Comparability/icd9_icd10/Comparability_Ratio_tables.xls
[xxv] https://wonder.cdc.gov/wonder/help/ucd.html#ICD-10%20113%20Cause%20List
[xxvi] https://www.cdc.gov/nchs/data/dvs/Multiple_Cause_Record_Layout_2016.pdf, page 19; The list actually has 118 mututally exclusive groups instead of 113.

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

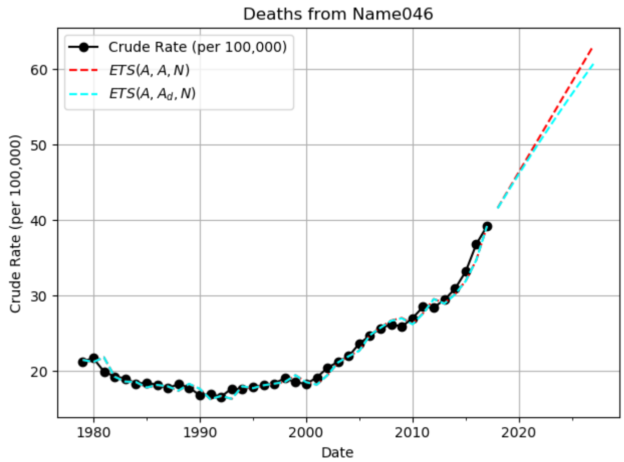

Figure 3: Highest priority action from the ICD-9 and ICD-10 113 Cause List for the United States: *Name046*

2. ICD-9 and ICD-10 113 Cause List for the United States, including subtotals in Table 9 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 9: $Z(t_F)$ table for the ICD-9 and ICD-10 113 Cause List for the United States, including subtotals

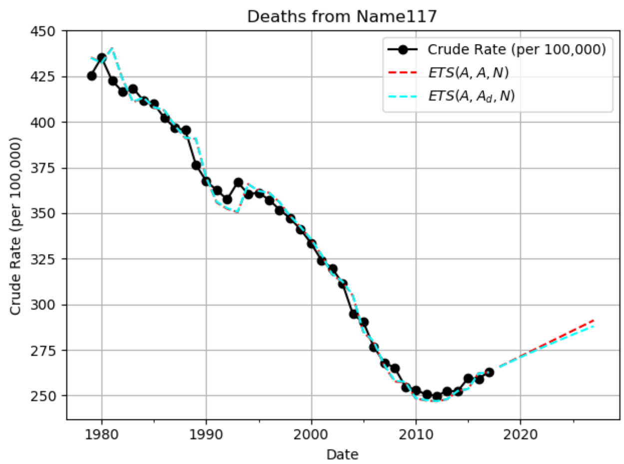

Figure 4: Highest priority action from the ICD-9 and ICD-10 113 Cause List for the United States, including subtotals: *Name117*

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

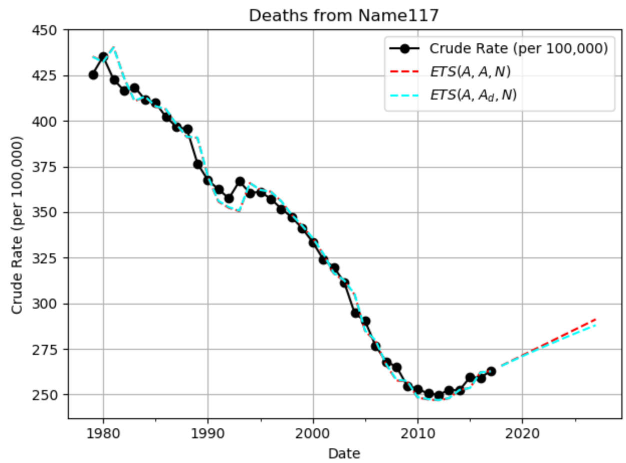

Figure 5: Highest priority action from the ICD-9 and ICD-10 113 Cause List for the United States with only top-level groupings: *Name117*

4. ICD-10 Chapters for the United States[53,xxvii] in Table 11 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 11: $Z(t_F)$ table for the ICD-10 Chapters for the United States

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

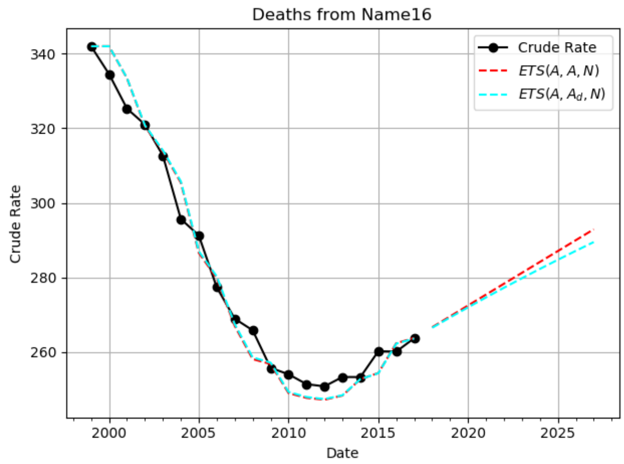

Figure 6: Highest priority action from the ICD-10 Chapters for the United States: *Name16*

5. ICD-10 Sub-Chapters for the United States[53,xxviii] in Table 12 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 12: $Z(t_F)$ table for the ICD-10 Sub-Chapters for the United States

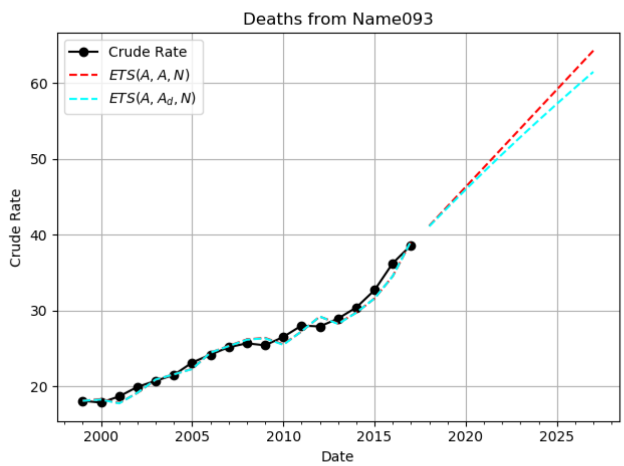

Figure 7: Highest priority action from the ICD-10 Sub-Chapters for the United States: *Name093*

6. Minimally grouped (5,264) causes of death for the United States[53,xxix,xxx] in Table 13 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 13: $Z(t_F)$ table for the Minimally grouped (5,264) causes of death for the United States

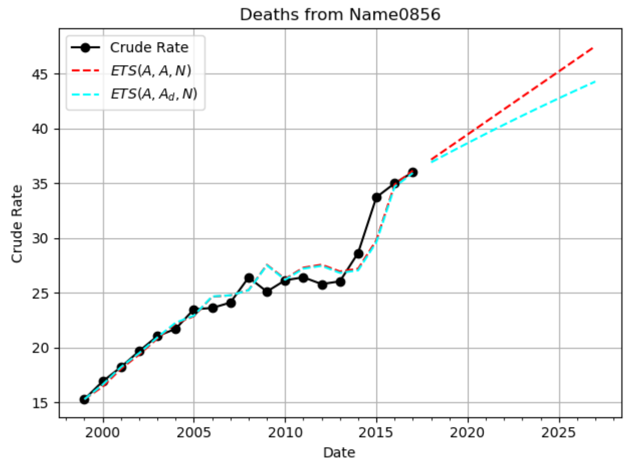

Figure 8: Highest priority action from the Minimally grouped (5,264) causes of death for the United States: *Name0856*

7. Minimally grouped (11,316) causes of death for the World[59,xxxi,xxxii,xxxiii] in Table 14 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 14: $Z(t_F)$ table for the Minimally grouped (11,316) causes of death for the World

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

[xxix] Group Results By "Year" And By "Cause of death"; Check "Export Results"; Uncheck "Show Totals"

[xxx] Without S_4 due to the sheer number of causes.

[xxxi] See Appendix command 7.

[xxxii] Without S_3 because comprehensive granular age data doesn't exist.

[xxxiii] Without S_4 due to the sheer number of causes.

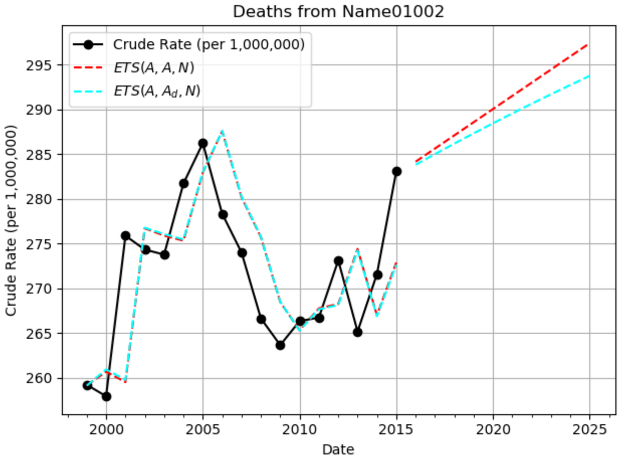

Figure 9: Highest priority action from the Minimally grouped (11,316) causes of death for the World: *Name01002*

8. ICD-10 Chapters for the World, including subtotals[59,xxxiv] in Table 15 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 15: $Z(t_F)$ table for the ICD-10 Chapters for the World, including subtotals

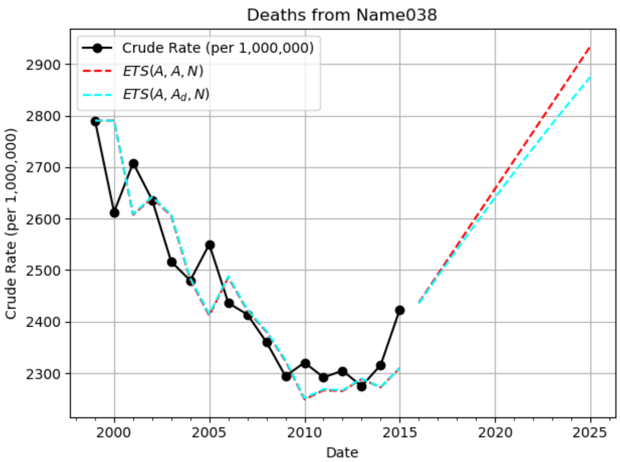

Figure 10: Highest priority action from the ICD-10 Chapters for the World, including subtotals: *Name038*

9. ICD-10 Chapters for the World with only top-level groupings[59,xxxv] in Table 16 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 16: $Z(t_F)$ table for the ICD-10 Chapters for the World with only top-level groupings

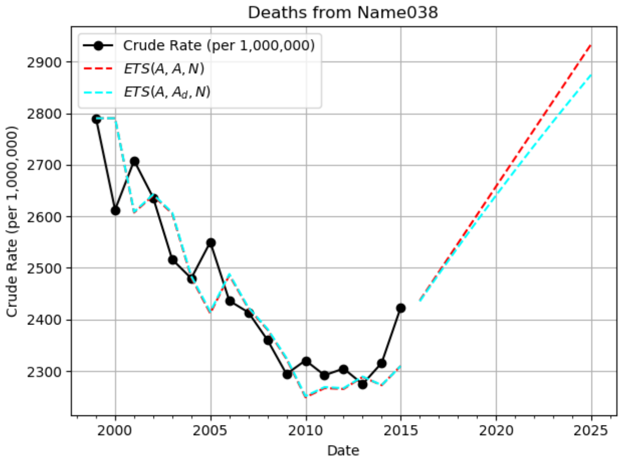

Figure 11: Highest priority action from the ICD-10 Chapters for the World with only top-level groupings: *Name038*

10. ICD-10 Sub-Chapters for the World[59,xxxvi] in Table 17 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 17: $Z(t_F)$ table for the ICD-10 Sub-Chapters for the World

[xxxiv] See footnote xxxii.
[xxxv] See footnote xxxii.
[xxxvi] See footnote xxxii.

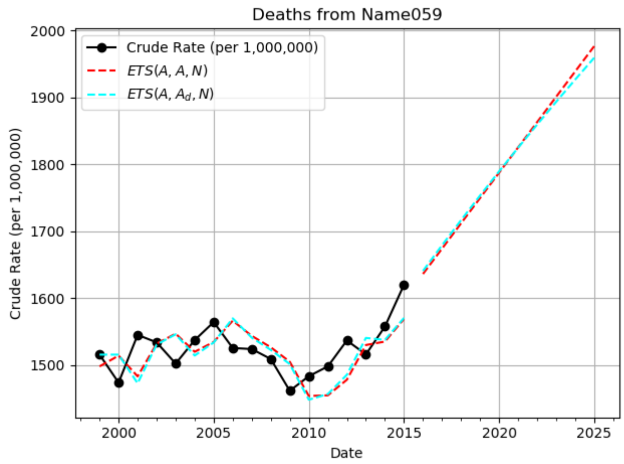

Figure 12: Highest priority action from the ICD-10 Sub-Chapters for the World: *Name059*

4. Discussion

This article proposes a method called value based prioritization which uses value theory to establish a goal and the set of known actions to accomplish said goal. Each action is relatively ranked based on some quantitative measurement(s) as called for by the same value theory. This ranking is transformed by a set of functions which scale up and down each action's relative score based on other relevant measurements and subjective opinions. The resulting list provides a prioritized relative ranking of actions that should be pursued in a particular order. Given that it may take significant time to ramp up and execute actions, modeled value based prioritization forecasts estimated relative rankings into the future to try to anticipate relative rankings by the time ramping up is complete. In essence, value based prioritization is a method to triage the proper actions to take given limited time and resources.

This method is applied to the example of choosing meaningful work using an example value system based on the goal to reduce human suffering. The method is sensitive to the choice of values and there are many ways to measure and scale the resulting relative rankings. Even with pretty clear measurements such as death, which is a binary and straightforward metric, there are endless questions about data quality ("Garbage In, Garbage Out"), how to define the underlying cause of death, which data sets to use ("e.g. would world death rates significantly change if political conditions changed?"), etc. Groupings of deaths introduce another dimension to evaluation: it's not clear how to relatively evaluate different groupings of deaths. Finally, there is a significant risk of missing actions that don't neatly categorize into measurable quantities. In short, there is no obvious way around certain philosophical questions, definitions, and evaluations.

Despite these shortcomings, alternative approaches are less quantitative, less explicit, and thus more difficult to evaluate and improve; and, more difficult to continuously evaluate progress on without such clear metrics. Further research and experience may help accumulate a database of value-metric mappings and scale functions that may be combined by people in different ways to help them find meaningful work.

References

[1] 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://doi.org/10.1080/17439760.2015.1137623.

[2] Roy F Baumeister. *Meanings of life*. Guilford Press, 1991.

[3] Viktor E Frankl. *Man's search for meaning*. Simon and Schuster, 1985.

[4] Roy F Baumeister, Kathleen D Vohs, Jennifer L Aaker, and Emily N Garbinsky. Some key differences between a happy life and a meaningful life. *The journal of positive psychology*, 8(6): 505–516, 2013. https://doi.org/10.1080/17439760.2013.830764.

[5] Crystal L Park and Login S George. Assessing meaning and meaning making in the context of stressful life events: Measurement tools and approaches. *The Journal of Positive Psychology*, 8 (6):483–504, 2013.

[6] Blake A Allan, Ryan D Duffy, and Richard Douglass. Meaning in life and work: A developmental perspective. *The Journal of Positive Psychology*, 10(4):323–331, 2015. https://doi.org/10.1080/17439760.2014.950180.

[7] Samantha J Heintzelman and Laura A King. On knowing more than we can tell: Intuitive processes and the experience of meaning. *The Journal of Positive Psychology*, 8(6):471–482, 2013. https://doi.org/10.1080/17439760.2013.830758.

[8] Michael F Steger. Experiencing meaning in life: Optimal functioning at the nexus of well-being, psychopathology, and spirituality. In *The human quest for meaning*, pages 211–230. Routledge, 2013.

[9] Bryan J Dik, Ryan D Duffy, and Brandy M Eldridge. Calling and vocation in career counseling: Recommendations for promoting meaningful work. *Professional Psychology: Research and Practice*, 40 (6):625, 2009. https://doi.org/10.1037/a0015547.

[10] Lindsay G Oades, Michael Steger, Antonelle Delle Fave, and Jonathan Passmore. *The Wiley Blackwell handbook of the psychology of positivity and strengths-based approaches at work*. John Wiley & Sons, 2017.

[11] Michael F Steger and Bryan J Dik. If one is looking for meaning in life, does it help to find meaning in work? *Applied Psychology: Health and Well-Being*, 1(3):303–320, 2009. https://doi.org/10.1111/j.1758-0854.2009.01018.x.

[12] Bryan J Dik and Ryan D Duffy. *Make your job a calling: How the psychology of vocation can change your life at work*. Templeton Foundation Press, 2012.

[13] Login S George and Crystal L Park. Are meaning and purpose distinct? an examination of correlates and predictors. *The Journal of Positive Psychology*, 8(5):365–375, 2013. https://doi.org/10.1080/17439760.2013.805801.

[14] Michael F Steger, Patricia Frazier, Shigehiro Oishi, and Matthew Kaler. The meaning in life questionnaire: Assessing the presence of and search for meaning in life. *Journal of counseling psychology*, 53(1):80, 2006. https://doi.org/10.1037/0022-0167.53.1.80.

[15] Martin EP Seligman. *Learned optimism: How to change your mind and your life*. Vintage, 2006.

[16] Paul TP Wong. Meaning therapy: An integrative and positive existential psychotherapy. *Journal of Contemporary Psychotherapy*, 40(2):85–93, 2010. https://doi.org/10.1007/s10879-009-9132-6.

[17] Jelena Zikic and Alan M Saks. Job search and social cognitive theory: The role of career-relevant activities. *Journal of Vocational Behavior*, 74(1): 117–127, 2009. https://doi.org/10.1016/j.jvb.2008.11.001.

[18] 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/.

[19] Michael Huemer. *Ethical Intuitionism*. Springer, 2007. https://spot.colorado.edu/~huemer/5.htm.

[20] 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/.

[21] 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/.

[22] 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/.

[23] 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/.

[24] 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/.

[25] 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/.

[26] Michael Huemer. *The Problem of Political Authority*. Springer, 2013. https://spot.colorado.edu/~huemer/1.htm.

[27] 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/.

[28] 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/.

[29] 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/.

[30] 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/.

[31] Jan G De Gooijer and Rob J Hyndman. 25 years of time series forecasting. *International journal of forecasting*, 22(3):443–473, 2006. https://doi.org/10.1016/j.ijforecast.2006.01.001.

[32] Leonard J Tashman and Michael L Leach. Automatic forecasting software: A survey and evaluation, 1991. https://doi.org/10.1016/0169-2070(91)90055-Z.

[33] Rob J Hyndman and George Athanasopoulos. *Forecasting: principles and practice*. OTexts, 2018. https://otexts.com/fpp2/.

[34] Sean J Taylor and Benjamin Letham. Forecasting at scale. *The American Statistician*, 72(1):37–45, 2018. https://doi.org/10.1080/00031305.2017.1380080.

[35] 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://doi.org/10.1111/j.1467-9574.2012.00530.x.

[36] 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/.

[37] 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://doi.org/10.1016/j.ijforecast.2018.06.001.

[38] 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://doi.org/10.1371/journal.pmed.0030442.

[39] Robert T Clemen. Combining forecasts: A review and annotated bibliography. *International journal of forecasting*, 5(4):559–583, 1989. https://doi.org/10.1016/0169-2070(89)90012-5.

[40] Milton C Weinstein, George Torrance, and Alistair McGuire. QALYs: the basics. *Value in health*, 12: S5–S9, 2009. https://doi.org/10.1111/j.1524-4733.2009.00515.x.

[41] 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/10986/7039/364010PAPER0Gl101OFFICIAL0USE0ONLY1.pdf.

[42] 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.

[43] 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://doi.org/10.12688/gatesopenres.12786.2.

[44] 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.

[45] 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.

[46] Nick Bostrom. Existential risk prevention as global priority. *Global Policy*, 4(1):15–31, 2013. http://www.existential-risk.org/concept.pdf.

[47] William MacAskill. *Doing good better: Effective altruism and a radical new way to make a difference*. Guardian Faber Publishing, 2015.

[48] 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.

[49] 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.

[50] 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.

[51] 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.

[52] 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.

[53] Centers for Disease Control and Prevention and National Center for Health Statistics. Underlying Cause of Death 1999-2017. https://wonder.cdc.gov/ucd-icd10.html. Accessed: 2019-03-01.

[54] 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.

[55] 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.

[56] Michael Huemer. In praise of passivity. *Studia Humana*, 1(2):12–28, 2012. http://studiahumana.com/pliki/wydania/In%20Praise%20of%20Passivity.pdf.

[57] 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.

[58] 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.

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

5. Appendix

Notes on Section 3:

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[xxxvii]:
   `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[xxxviii] 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:

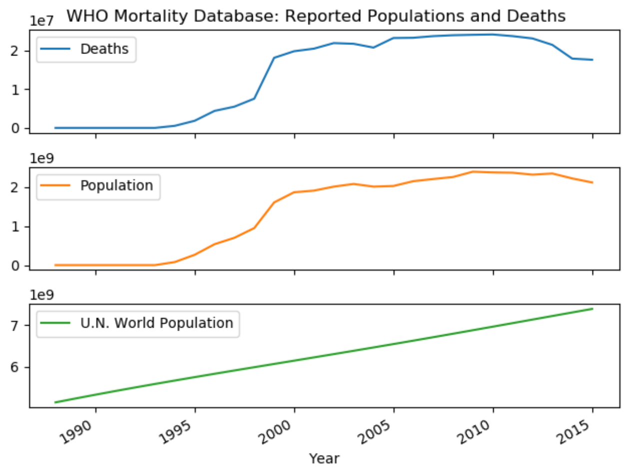

Figure 13: WHO Mortality Database: Reported Population and Deaths

4. "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 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."[38]

5. "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."[38]

6. "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."[xxxix]

[xxxvii] https://www.cdc.gov/nchs/data/dvs/lead1900_98.pdf
[xxxviii] https://seer.cancer.gov/seerstat/tutorials/aarates/definition.html
[xxxix] https://apps.who.int/healthinfo/statistics/mortality/whodpms/help/desc.htm

5.1. Python Commands

1. `python3 -m vbp.run list UCODUnitedStates`
2. `python3 -m vbp.run manual_scale_functions -a -t excel -o manual_scale_functions.xlsx -n "Scale Values" -p "Eliminate:  " UCODUnitedStates S4`
3. `python3 -m vbp.run action_data UCODUnitedStates Cancer`
4. `python3 -m vbp.run predict UCODUnitedStates --ets-no-multiplicative-models --do-not-obfuscate -p 10 Cancer`
5. `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`
6. `python3 -m vbp.run modeled_value_based_prioritization -a UCODUnitedStates ...`
7. `python3 -m vbp.run modeled_value_based_prioritization UCODWorld --ets-no-multiplicative-models -k 5 -p 10 --manual-scales manual_scale_functions.xlsx`