Post-mortem memory of public figures in news and social media

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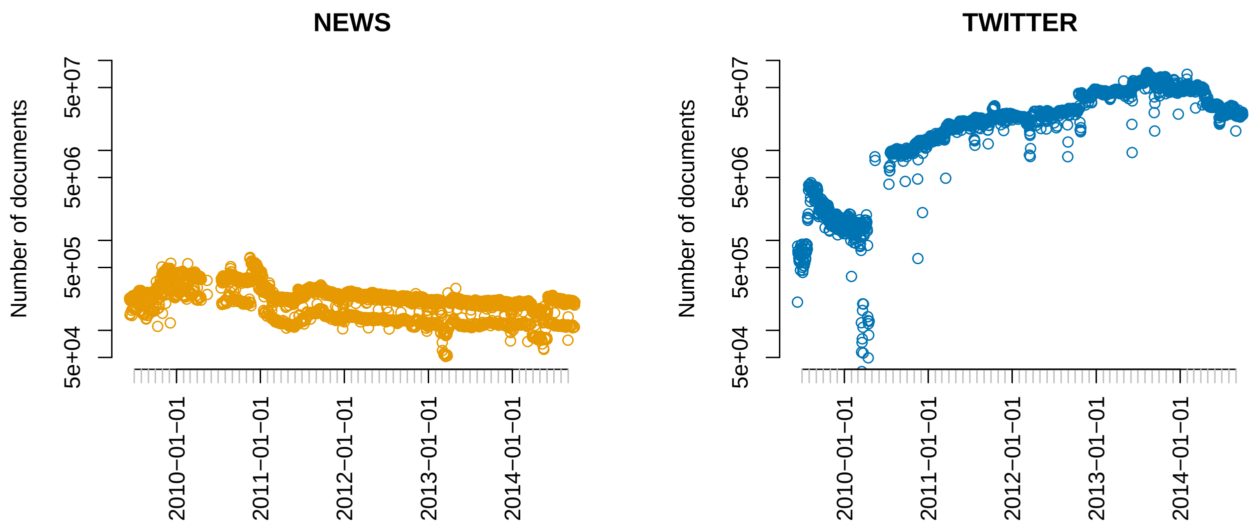
Number of documents per day



Supplementary Figure 1: Number of documents per day in the Spinn3r corpus.

Taxonomy of causes of death

Natural causes of death

Acute myeloid leukemia, Adrenocortical carcinoma, Alveolar rhabdomyosarcoma, Alzheimer's disease, Amyloidosis, Amyotrophic lateral sclerosis, Anemia, Aneurysm, Aortic aneurysm, Aortic dissection, Appendix cancer, Asthma, Astrocytoma, Atherosclerosis, Atypical teratoid rhabdoid tumor, B-cell chronic lymphocytic leukemia, Bladder cancer, Bleeding, Blood disorder, Blunt trauma, Bone cancer, Bone tumor, Brain Cancer, Brain damage, Brain tumor, Breast cancer, Bronchitis, Bronchopneumonia, Cancer, Cardiac arrest, Cardiac dysrhythmia, Cardiac surgery, Cardiopulmonary Arrest, Cardiovascular disease, Cerebral hemorrhage, Cerebral infarction, Cervical cancer, Cholangiocarcinoma, Chronic kidney disease, Chronic Obstructive Pulmonary Disease, Cirrhosis, Colorectal cancer, Complication, Complications from a stroke, Complications from cardiac surgery, Complications from pneumonia, Complications of diabetes mellitus, Congenital heart defect, Coronary artery disease, Craniocerebral Trauma, Creutzfeldt–Jakob disease, Cystic fibrosis, Dementia, Dementia with Lewy bodies, Diabetes mellitus, Disease, Ebola virus disease, Emphysema, Epileptic seizure, Esophageal cancer, Gallbladder cancer, Glioblastoma multiforme, Heart Ailment, Heart failure, Heart valve disease, Heat Stroke, Hepatitis, HIV/AIDS, Hodgkin's lymphoma, Huntington's disease, Hypertension, Hypertensive heart disease, Hyperthermia, Illness, Infection, Influenza, Internal bleeding, Intracranial aneurysm, Intracranial hemorrhage, Kidney cancer, Laryngeal cancer, Leiomyosarcoma, Leukemia, Liver cancer, Liver disease, Liver failure, Liver tumour, Lung cancer, Lung disease, Lung Infection, Lymphoma, Malaria, Melanoma, Meningitis, Mesothelioma, Metastatic breast cancer, Metastatic Melanoma, Motor neuron disease, Multiple myeloma, Multiple organ dysfunction syndrome, Multiple organ failure, Multiple sclerosis, Multiple system atrophy, Myelodysplastic syndrome, Myocardial infarction, Natural causes, Nephropathy, Non-Hodgkin lymphoma, Old age, Oral cancer, Organ dysfunction, Ovarian cancer, Pancreatic cancer, Pancreatitis, Parkinson's disease, Peritonitis, Pneumonia, Pneumothorax, Polycythemia, Polymyalgia rheumatica, Progressive supranuclear palsy, prolonged illness, Prostate cancer, Pulmonary edema, Pulmonary embolism, Pulmonary failure, Pulmonary fibrosis, Pyelonephritis, Renal failure, Respiratory arrest, Respiratory disease, Respiratory failure, Salivary gland neoplasm, Sepsis, Septic shock, Skin cancer, Smallpox, Squamous-cell carcinoma, Stomach cancer, Stroke, Subarachnoid hemorrhage, Subdural hematoma, Surgery, Surgical complications, T-Cell Lymphoma, Terminal illness, Throat Cancer, Thrombosis, Thrombus, Thyroid cancer, Urinary tract infection, Uterine cancer, Vascular dementia, Viral pneumonia

Unnatural causes of death

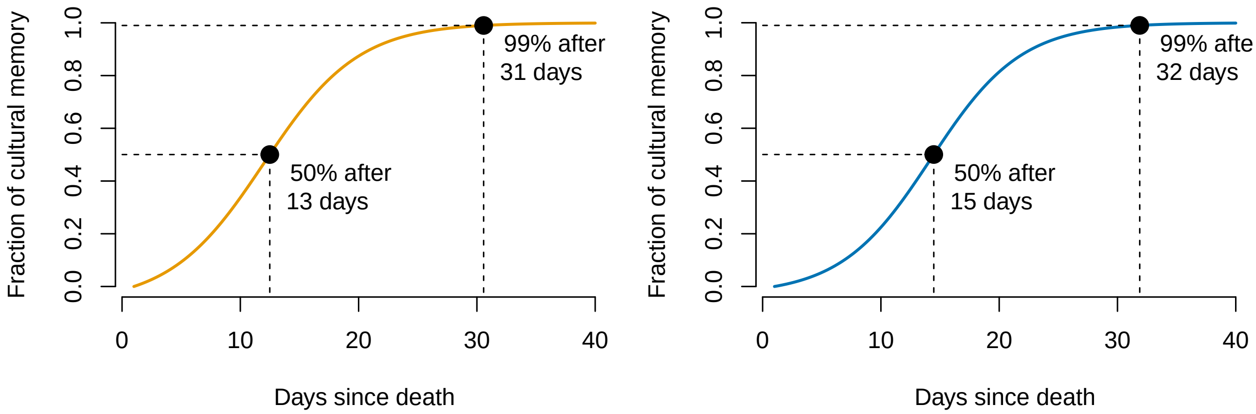
Accident, Accidental drug overdose, Accidental fall, Airstrike, Alcohol intoxication, Ambush, Asphyxia, Assassination, Assisted suicide, Aviation accident or incident, Ballistic trauma, Bike accident, Blast injury, Boating Accident, Bomb, Brain injury, Capital punishment, Car bomb, Carbon monoxide poisoning, Casualty of war, Cocaine overdose, Combined drug intoxication, Decapitation, Drowning, Drug overdose, Execution, Execution by firing squad, Execution-style murder, Explosion, Falling, Falling from height, Fire, Firearm, Gunshot, Hanging, Helicopter crash, Heroin overdose, Hit and run, Homicide, Improvised bombing, Injury, Killed in action, Lethal injection, Lightning, Major trauma, Motorcycle accident, Mountaineering, Murder, Murder_suicide, Murder–suicide, Poison, Poisoning, Racing Accident, Self-inflicted wound, Shark attack, Shootout, Skiing accident, Smoke inhalation, Stab wound, Stabbing, Strangling, Struck by car, Suicide, Suicide attack, Suicide by hanging, Tornado Incident, Torture, Traffic collision, Traumatic brain injury

Taxonomy of notability types

- **academia/engineering:** Academic, Aircraft designer, Amusement Ride Designer, Astronaut, Astronomer, Computer Scientist, Honorary Degree Recipient, Invention, Inventor, Physician, Surgeon, Translator
- **art:** Architect, Author, Automotive Designer, Bassist, Blogger, Book, Broadcast Artist, Chef, Collector, Comic Book Colorist, Comic Book Creator, Comic Book Inker, Comic Book Letterer, Comic Book Penciler, Comic Book Writer, Comic Strip Creator, Composer, Conductor, Drummer, Fashion designer, Fictional Character Creator, Film actor, Film art director, Film casting director, Film cinematographer, Film costumer designer, Film crewmember, Film critic, Film director, Film editor, Film music contributor, Film producer, Film production designer, Film set decorator, Film story contributor, Film subject, Film writer, Game designer, Guitarist, Hobbyist, Illustrator, Lyricist, Museum director, Music video director, Music video performer, Musical Artist, Musician, Newspaper Owner, Opera Director, Opera singer, Periodical editor, Person or entity appearing in film, Record Producer, Recording Engineer, Ship Designer, Songwriter, Theater Actor, Theater Choreographer, Theater Designer, Theater Director, Theater Producer, TV Actor, TV Character, TV Director, TV Personality, TV Producer, TV Program Creator, TV program guest, TV station owner, TV subject, TV Writer, Video Game Actor, Video Game Designer, Visual Artist
- **general fame:** Appointee, Award Nominee, Award Winner, Celebrity, Competitor, Deity, Department, Event, Family member, Family name, Hall of fame inductee, Interviewee, Literature Subject, Noble person, Organization member, Person, Person Or Being In Fiction, Project participant, Quotation Subject, Shareholder, Social network user, Sponsored Recipient
- **known for death:** Deceased Person, Disaster survivor, Disaster victim
- **leadership:** Chivalric Order Member, Judge, Military Commander, Military Person, Monarch, Organization founder, Organization leader, Politician, Religious Leader, Religious Leadership Role, U.S. Congressperson
- **sports:** American football head coach, American football player, Athlete, Australian Rules Footballer, Baseball Coach, Baseball Manager, Baseball Player, Basketball Coach, Basketball Player, Boxer, Chess

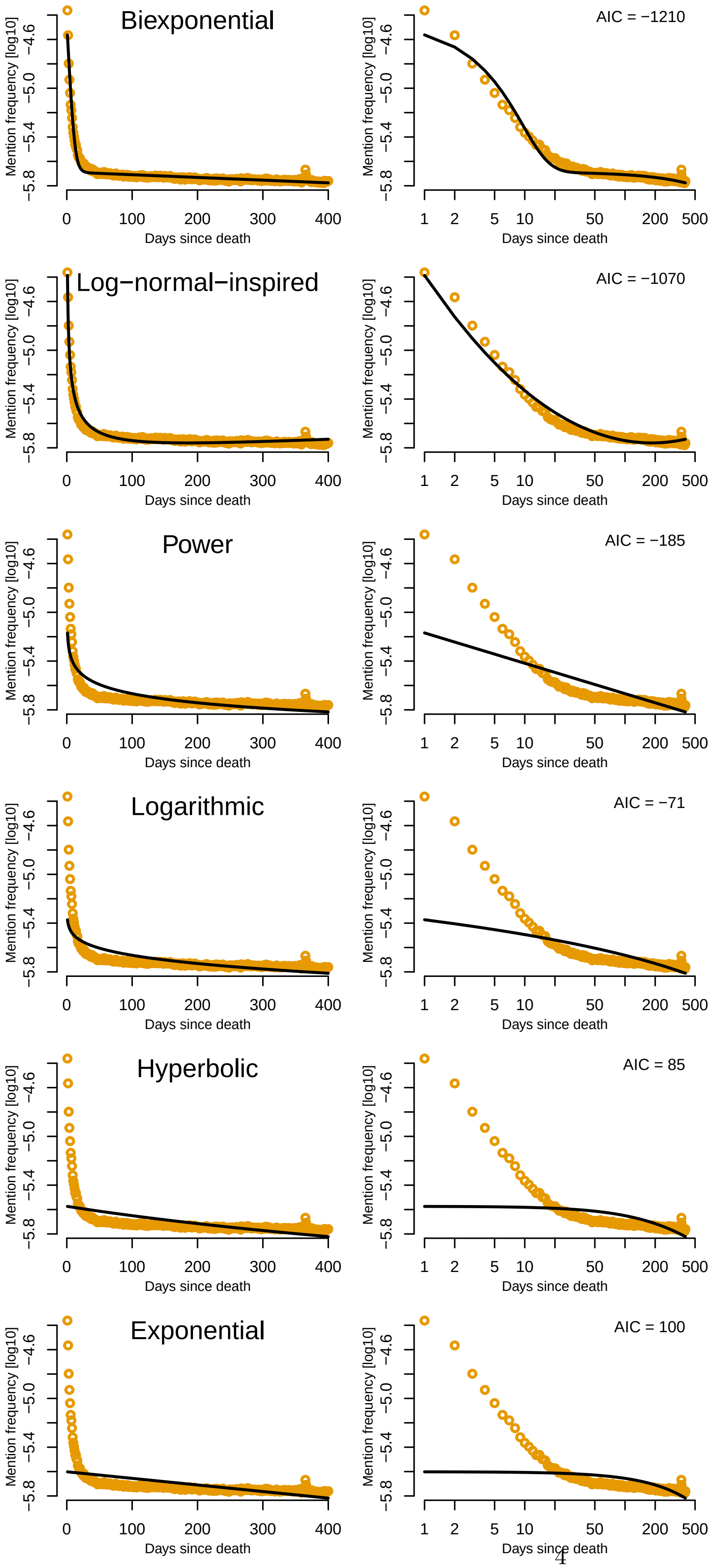
Player, Cricket Bowler, Cricket Player, Cricket Umpire, Cyclist, Drafted athlete, Football player, Football team manager, Golf Course Architect, Golfer, Ice hockey coach, Ice hockey player, Martial Artist, Mountaineer, Olympic athlete, Sports League Award Winner, Sports official, Sports team coach, Sports Team Owner, Tennis Player, Tennis Tournament Champion

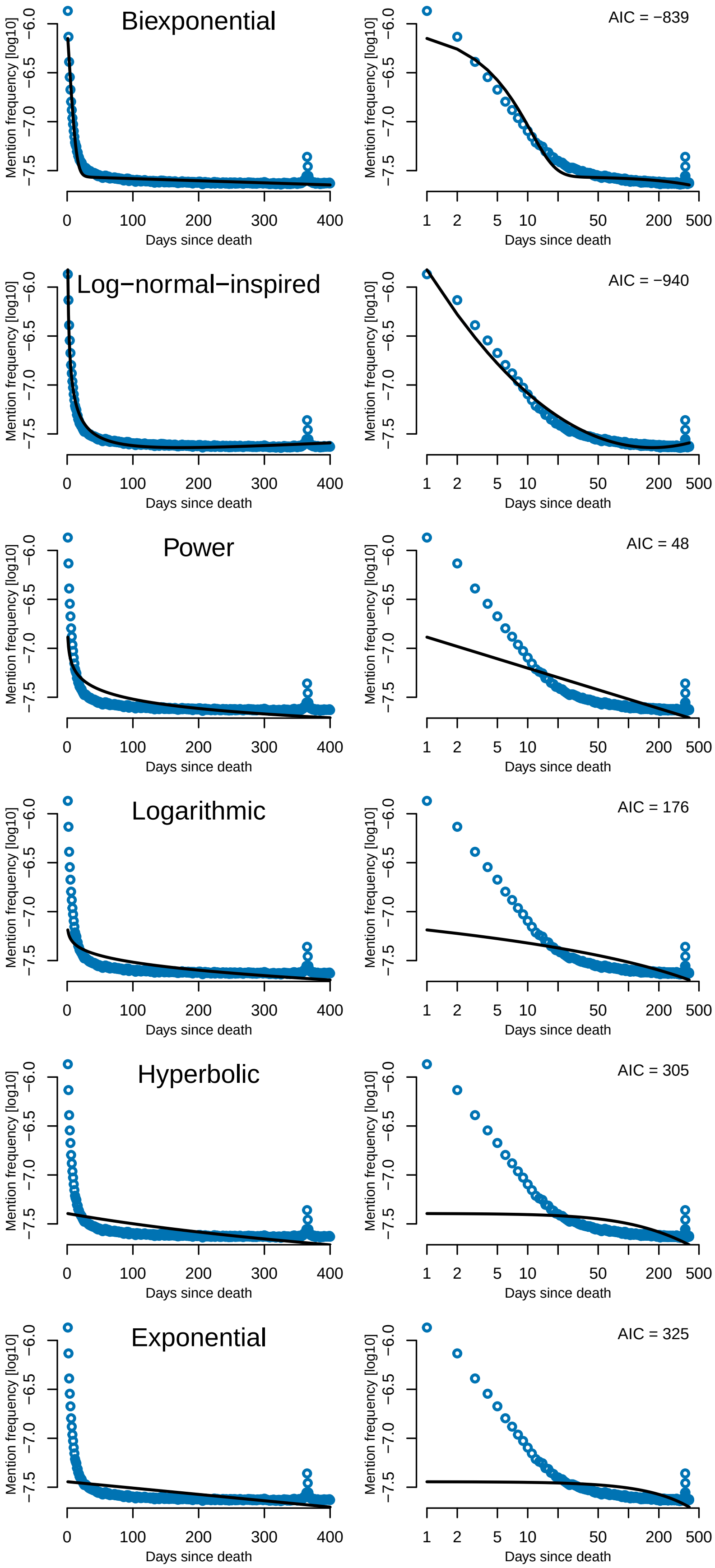
Proportion of cultural vs. communicative memory



Supplementary Figure 2: Proportion of cultural vs. communicative memory. On day t after death, the total collective memory according to the biexponential model fit is $S(t) = u(t) + v(t)$, where $u(t)$ is the communicative memory, and $v(t)$ is the cultural memory. We plot the proportion $v(t)/S(t)$ as a function of t. *Left:* news. *Right:* Twitter.

Alternative models




Biexponential
AIC = −839
Log−normal−inspired
AIC = −940
Power
AIC = 48
Logarithmic
AIC = 176
Hyperbolic
AIC = 305
Exponential
AIC = 325
Mention frequency [log10]
Days since death

Supplementary Figure 3: Comparison of six models $S(t)$ for fitting empirical mention frequencies. *Top (yellow):* news. *Bottom (blue):* Twitter. The left and right plots in each row show the same fits, the only difference being that the left plots have linear x-axes, whereas the right plots have logarithmic x-axes. Fits are nonlinear least-squares fits obtained in log space, i.e., logarithms were taken of both the data and the model $S(t)$ before performing the least-squares optimization (see equation (5) in the paper for the case of the biexponential model). The biexponential function is defined in equation (4) of the paper. The other functions are defined as follows: Log-normal-inspired: $S(t) = \exp(a' - b\log t + c(\log t)^2) = a\,t^{-b+c\log t}$. Power: $S(t) = a\,t^{-b}$. Logarithmic: $S(t) = a - b\log t$. Hyperbolic: $S(t) = (a + bt)^{-1}$. Exponential: $S(t) = a\,e^{-bt}$. Akaike's information criterion (AIC), shown in the right plots, captures goodness of fit while accounting for model complexity (smaller AIC values correspond to better fits). The biexponential model fits the data best in the case of the news (AIC difference = 140), whereas the log-normal-inspired model fits the data best in the case of Twitter (AIC difference = 101). Note, however, that the log-normal-inspired model is the only one to have the undesirable property of being non-monotonic, unlike the empirical data and unlike what one would require from a theoretical model.

Mention time series characteristics

Summaries of distributions of mention time series characteristics

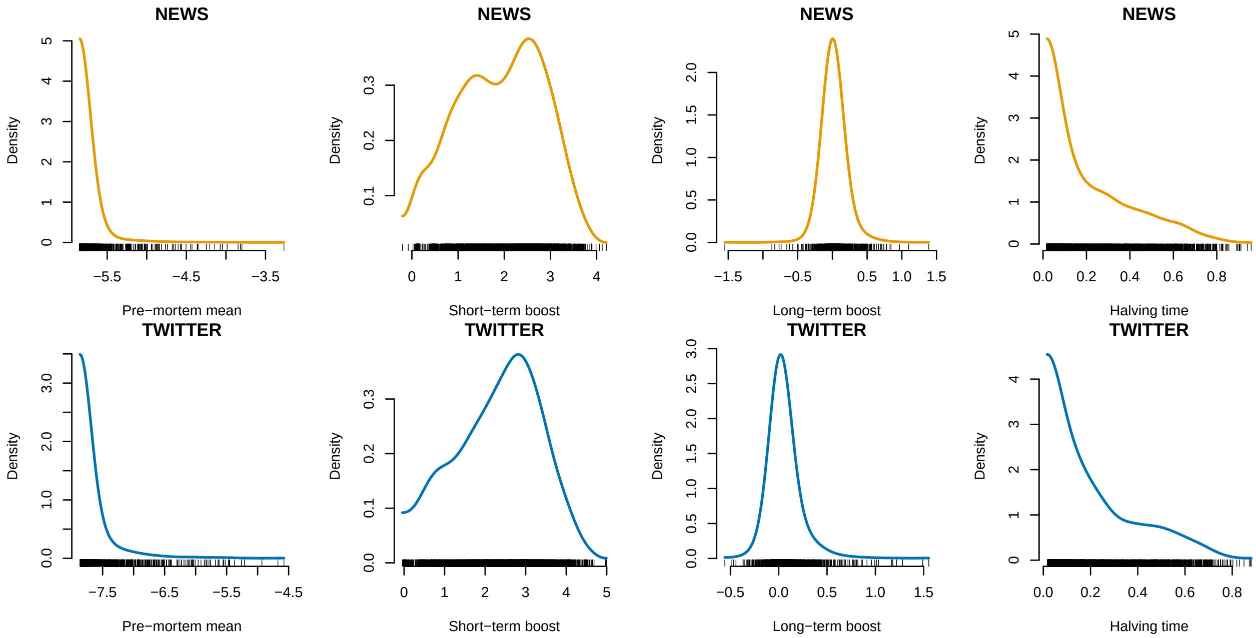
(a) News

```
##  Pre-mortem mean  Short-term boost  Long-term boost      Halving time
##  Min.   :-5.851   Min.   :-0.2055   Min.   :-1.5490200   Min.   :0.01667
##  1st Qu.:-5.835   1st Qu.: 1.1924   1st Qu.:-0.0147554   1st Qu.:0.05903
##  Median :-5.819   Median : 1.9754   Median : 0.0005455   Median :0.16111
##  Mean   :-5.755   Mean   : 1.9171   Mean   : 0.0191381   Mean   :0.23172
##  3rd Qu.:-5.770   3rd Qu.: 2.6687   3rd Qu.: 0.0270671   3rd Qu.:0.35833
##  Max.   :-3.267   Max.   : 4.2103   Max.   : 1.3884812   Max.   :0.95833
```

(b) Twitter

```
##  Pre-mortem mean  Short-term boost  Long-term boost     Halving time
##  Min.   :-7.866   Min.   :-0.0413   Min.   :-0.557536   Min.   :0.01667
##  1st Qu.:-7.839   1st Qu.: 1.5856   1st Qu.:-0.006985   1st Qu.:0.06667
##  Median :-7.803   Median : 2.4474   Median : 0.016047   Median :0.15972
##  Mean   :-7.664   Mean   : 2.3262   Mean   : 0.055143   Mean   :0.22363
##  3rd Qu.:-7.671   3rd Qu.: 3.0998   3rd Qu.: 0.077694   3rd Qu.:0.33611
##  Max.   :-4.576   Max.   : 4.9904   Max.   : 1.552516   Max.   :0.88056
```

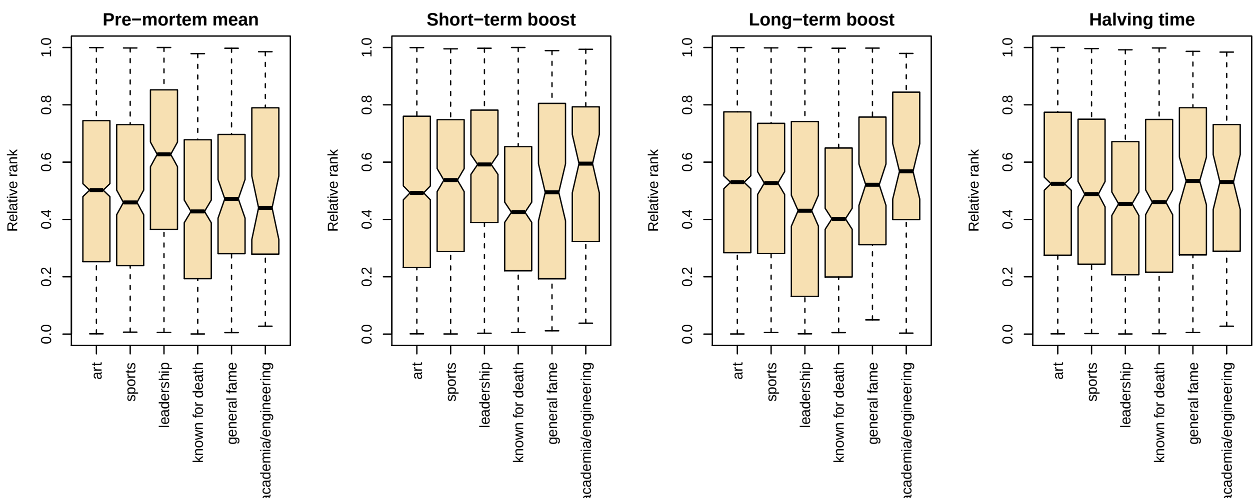
Supplementary Table 1: Summaries of distribution of mention time series characteristics for **(a)** the news and **(b)** Twitter.



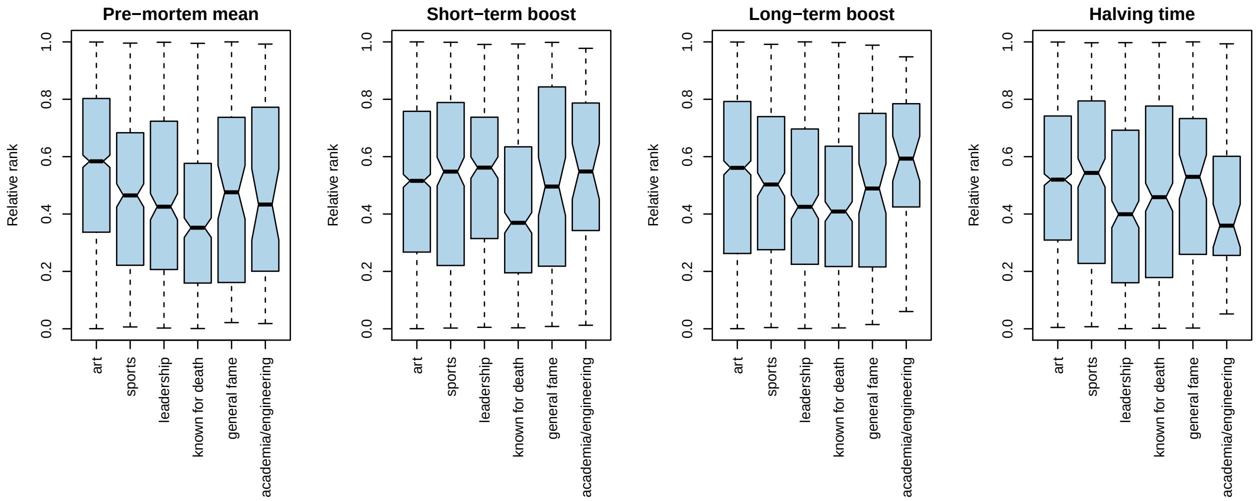
Supplementary Figure 4: Kernel-smoothed density plots of mention time series characteristics for the news (top) and Twitter (bottom).

Mention time series characteristics by notability type

(a) News



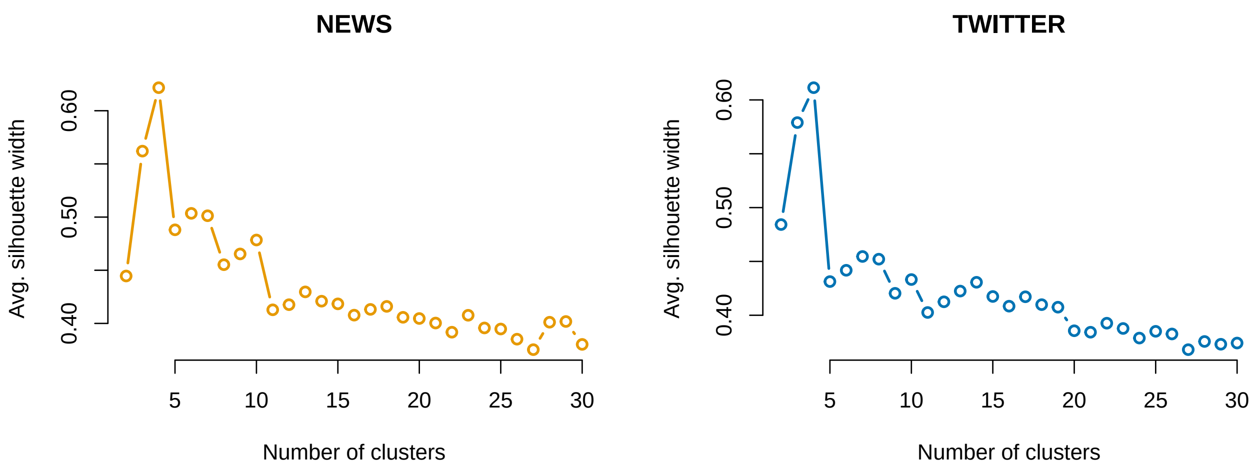
(b) Twitter



Supplementary Figure 5: Distributions of mention time series characteristics by notability type, visualized as box plots, for **(a)** the news and **(b)** Twitter. Boxes are bounded by the first and third quartiles; whiskers extend 1.5 inter-quartile ranges beyond the first and third quartiles (or to the minimum/maximum in case they fall within 1.5 inter-quartile ranges); the center bars mark medians, with notches corresponding to 95% confidence intervals of the median.

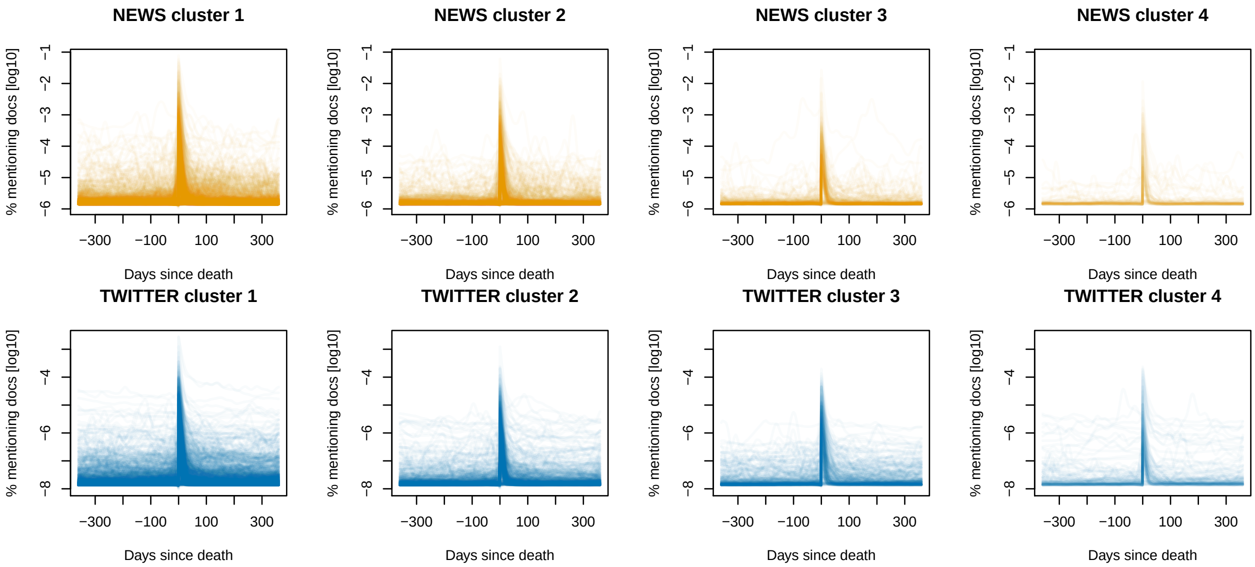
Cluster analysis

Optimal number of clusters



Supplementary Figure 6: Average silhouette width of clusterings produced by k-means algorithm, as a function of the number k of clusters (higher is better), for $k \in \{2, \ldots, 30\}$. Both **(a)** in the news and **(b)** on Twitter, $k = 4$ is optimal.

Overlay of time series per cluster



Supplementary Figure 7: Overlay of time series in each cluster, for news (top) and Twitter (bottom).

Regression modeling

Note: the variable names in the code may differ from those in the paper; see mapping in lists below.

Independent variables:

- pre-mortem mean (`mean_before`)
- age at death (`age_group`)
- manner of death (`death_type`)
- notability type (`type_group`)
- cultural background (`anglo`)
- gender (`gender`)

Dependendent variables:

- short-term boost (`peak_mean_boost`)
- long-term boost (`perm_boost`)

Models without interactions

```
##
## Call:
## lm(formula = as.formula(sprintf("peak_mean_boost_relrank ~ %s",
##     predictors)), data = lmdata_N)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.62044 -0.19422  0.01128  0.20580  0.74237
##
## Coefficients:
##                                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)                       0.001595   0.020820   0.077   0.9390
```

```
## mean_before_relrank            0.292185   0.030757   9.500  < 2e-16 ***
## age_group20                    0.054393   0.056290   0.966   0.3342    
## age_group30                    0.119792   0.055379   2.163   0.0308 *  
## age_group40                   -0.020965   0.041680  -0.503   0.6151    
## age_group50                   -0.029145   0.032728  -0.891   0.3734    
## age_group60                   -0.046225   0.027036  -1.710   0.0877 .  
## age_group80                    0.011330   0.025892   0.438   0.6618    
## age_group90                    0.070412   0.032351   2.177   0.0298 *  
## death_typeunnatural            0.223393   0.031296   7.138 2.03e-12 ***
## genderFemale                   0.032258   0.023861   1.352   0.1768    
## anglonon_anglo                -0.100770   0.024407  -4.129 4.01e-05 ***
## anglounknown                  -0.149597   0.028286  -5.289 1.57e-07 ***
## type_groupacademia/engineering  0.054180   0.065320   0.829   0.4071    
## type_groupgeneral fame         0.025013   0.040994   0.610   0.5419    
## type_groupknown for death     -0.041843   0.032861  -1.273   0.2033    
## type_groupleadership           0.027634   0.027408   1.008   0.3136    
## type_groupsports               0.001862   0.027579   0.068   0.9462    
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2555 on 852 degrees of freedom
## Multiple R-squared:  0.2343, Adjusted R-squared:  0.219 
## F-statistic: 15.34 on 17 and 852 DF,  p-value: < 2.2e-16
```

Supplementary Table 2: Linear regression model of short-term boost in the news.

```
##
## Call:
## lm(formula = as.formula(sprintf("     perm_boost_relrank ~ %s", 
##     predictors)), data = lmdata_N)
##
## Residuals:
##      Min       1Q   Median       3Q      Max 
## -0.60548 -0.21923  0.00579  0.23231  0.57350 
##
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)    
## (Intercept)                    0.069386   0.022386   3.099 0.002002 ** 
## mean_before_relrank           -0.035601   0.033071  -1.076 0.282009    
## age_group20                    0.014011   0.060525   0.231 0.816994    
## age_group30                   -0.025187   0.059546  -0.423 0.672407    
## age_group40                   -0.043987   0.044816  -0.982 0.326618    
## age_group50                   -0.116348   0.035190  -3.306 0.000985 ***
## age_group60                   -0.085145   0.029070  -2.929 0.003491 ** 
## age_group80                   -0.009021   0.027840  -0.324 0.745990    
## age_group90                    0.039381   0.034785   1.132 0.257902    
## death_typeunnatural            0.134966   0.033651   4.011 6.58e-05 ***
## genderFemale                   0.037946   0.025656   1.479 0.139504    
## anglonon_anglo                -0.108631   0.026244  -4.139 3.83e-05 ***
## anglounknown                  -0.145758   0.030415  -4.792 1.94e-06 ***
## type_groupacademia/engineering -0.019779   0.070235  -0.282 0.778306    
## type_groupgeneral fame        -0.002759   0.044079  -0.063 0.950104    
```

```
## type_groupknown for death      -0.064889   0.035334  -1.836 0.066638 .
## type_groupleadership           -0.071294   0.029470  -2.419 0.015763 *
## type_groupsports               -0.042940   0.029654  -1.448 0.147977
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2748 on 852 degrees of freedom
## Multiple R-squared:  0.1148, Adjusted R-squared:  0.0971
## F-statistic: 6.498 on 17 and 852 DF,  p-value: 1.155e-14
```

Supplementary Table 3: Linear regression model of long-term boost in the news.

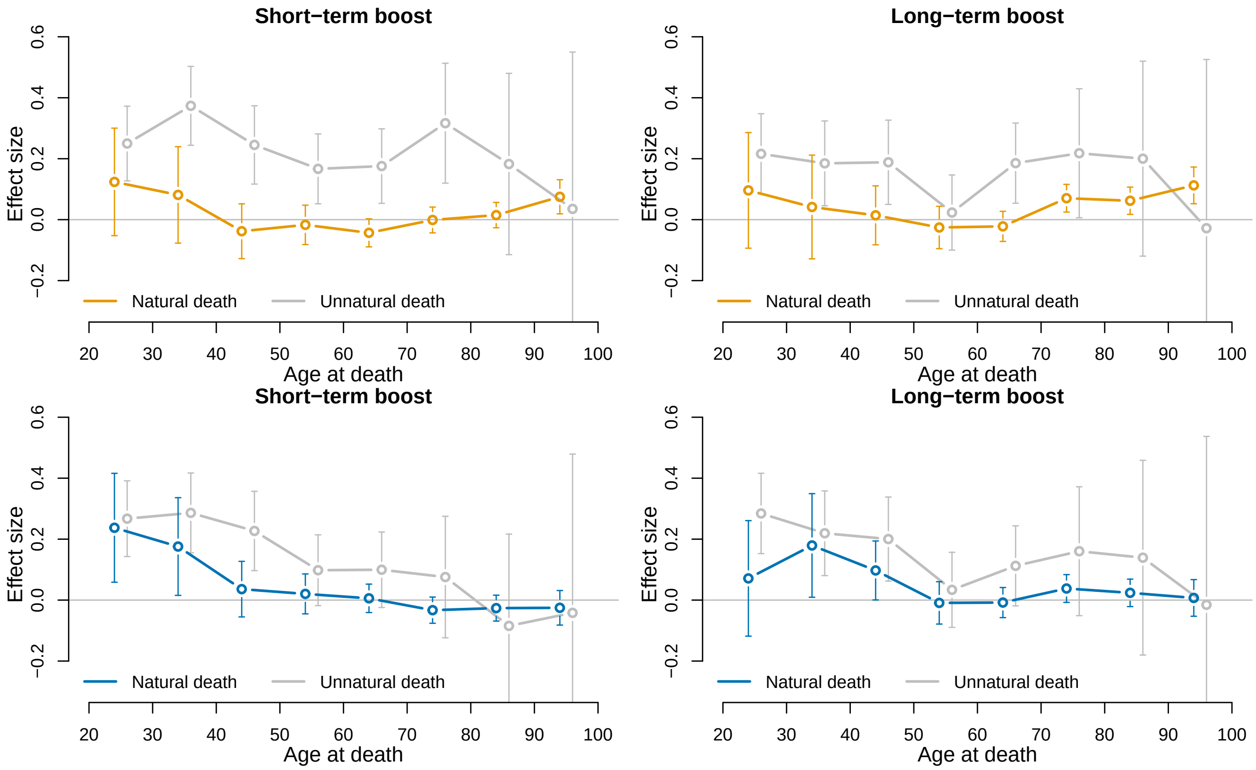
```
##
## Call:
## lm(formula = as.formula(sprintf("peak_mean_boost_relrank ~ %s",
##     predictors)), data = lmdata_T)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.71673 -0.18473 -0.00208  0.20710  0.61854
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    -0.033516   0.021153  -1.584 0.113459
## mean_before_relrank             0.336775   0.031589  10.661  < 2e-16 ***
## age_group20                     0.224402   0.056963   3.939 8.84e-05 ***
## age_group30                     0.216619   0.056034   3.866 0.000119 ***
## age_group40                     0.099944   0.042134   2.372 0.017910 *
## age_group50                     0.048430   0.033115   1.462 0.143973
## age_group60                     0.038284   0.027326   1.401 0.161574
## age_group80                     0.003695   0.026169   0.141 0.887740
## age_group90                     0.006365   0.032745   0.194 0.845930
## death_typeunnatural             0.095068   0.031662   3.003 0.002756 **
## genderFemale                   -0.007467   0.024089  -0.310 0.756643
## anglonon_anglo                 -0.030620   0.024636  -1.243 0.214240
## anglounknown                   -0.107934   0.028809  -3.746 0.000191 ***
## type_groupacademia/engineering  0.120612   0.066075   1.825 0.068295 .
## type_groupgeneral fame          0.052868   0.041492   1.274 0.202944
## type_groupknown for death      -0.026970   0.033516  -0.805 0.421209
## type_groupleadership            0.025037   0.027535   0.909 0.363470
## type_groupsports                0.026369   0.028019   0.941 0.346917
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2586 on 852 degrees of freedom
## Multiple R-squared:  0.2161, Adjusted R-squared:  0.2004
## F-statistic: 13.82 on 17 and 852 DF,  p-value: < 2.2e-16
```

Supplementary Table 4: Linear regression model of short-term boost on Twitter.

```
##
## Call:
## lm(formula = as.formula(sprintf("     perm_boost_relrank ~ %s",
##     predictors)), data = lmdata_T)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.67278 -0.19342  0.02505  0.21969  0.60132
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                     0.038607   0.022426   1.722 0.085511 .
## mean_before_relrank             0.118846   0.033490   3.549 0.000408 ***
## age_group20                     0.111425   0.060390   1.845 0.065372 .
## age_group30                     0.106071   0.059405   1.786 0.074526 .
## age_group40                     0.060312   0.044669   1.350 0.177307
## age_group50                    -0.060151   0.035107  -1.713 0.087008 .
## age_group60                    -0.044402   0.028970  -1.533 0.125726
## age_group80                    -0.015164   0.027744  -0.547 0.584804
## age_group90                    -0.033081   0.034715  -0.953 0.340897
## death_typeunnatural             0.096865   0.033567   2.886 0.004004 **
## genderFemale                    0.029224   0.025538   1.144 0.252806
## anglonon_anglo                 -0.031642   0.026118  -1.212 0.226027
## anglounknown                   -0.139591   0.030542  -4.570 5.59e-06 ***
## type_groupacademia/engineering  0.076049   0.070050   1.086 0.277952
## type_groupgeneral fame          0.006527   0.043988   0.148 0.882072
## type_groupknown for death      -0.025012   0.035532  -0.704 0.481664
## type_groupleadership           -0.102206   0.029192  -3.501 0.000487 ***
## type_groupsports               -0.025534   0.029704  -0.860 0.390257
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2741 on 852 degrees of freedom
## Multiple R-squared:  0.1189, Adjusted R-squared:  0.1013
## F-statistic: 6.765 on 17 and 852 DF,  p-value: 2.014e-15
```

Supplementary Table 5: Linear regression model of long-term boost on Twitter.

Models with "age by manner of death" interaction



Supplementary Figure 8: Dependence of post-mortem mention frequency on age at death for news (top) and Twitter (bottom).

```
##
## Call:
## lm(formula = as.formula(sprintf("peak_mean_boost_relrank ~ %s",
##     predictors)), data = lmdata)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.62147 -0.19550  0.01088  0.20087  0.73057
##
## Coefficients:
##                                     Estimate Std. Error t value Pr(>|t|)
## mean_before_relrank                0.2876073  0.0310288   9.269  < 2e-16 ***
## age_group70                       -0.0010522  0.0211400  -0.050  0.96031
## age_group20                        0.1238746  0.0881930   1.405  0.16051
## age_group30                        0.0812147  0.0791111   1.027  0.30491
## age_group40                       -0.0379687  0.0449768  -0.844  0.39881
## age_group50                       -0.0170764  0.0323044  -0.529  0.59722
## age_group60                       -0.0432214  0.0229844  -1.880  0.06039 .
## age_group80                        0.0149510  0.0207886   0.719  0.47222
## age_group90                        0.0749740  0.0279819   2.679  0.00752 **
## death_typeunnatural                0.3175289  0.0993996   3.194  0.00145 **
## genderFemale                       0.0340646  0.0239914   1.420  0.15602
```

```
## anglonon_anglo                   -0.1047908  0.0247235  -4.239  2.5e-05 ***
## anglounknown                     -0.1532241  0.0284546  -5.385  9.4e-08 ***
## type_groupacademia/engineering    0.0530173  0.0654330   0.810  0.41802
## type_groupgeneral fame            0.0191595  0.0412557   0.464  0.64247
## type_groupknown for death        -0.0403775  0.0330598  -1.221  0.22229
## type_groupleadership              0.0299099  0.0275100   1.087  0.27724
## type_groupsports                 -0.0005107  0.0277366  -0.018  0.98531
## age_group20:death_typeunnatural -0.1915827  0.1440851  -1.330  0.18399
## age_group30:death_typeunnatural -0.0252587  0.1410809  -0.179  0.85795
## age_group40:death_typeunnatural -0.0343547  0.1252681  -0.274  0.78396
## age_group50:death_typeunnatural -0.1337441  0.1183163  -1.130  0.25863
## age_group60:death_typeunnatural -0.0985255  0.1169552  -0.842  0.39979
## age_group80:death_typeunnatural -0.1499235  0.1799365  -0.833  0.40497
## age_group90:death_typeunnatural -0.3572365  0.2769449  -1.290  0.19743
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2559 on 845 degrees of freedom
## Multiple R-squared:  0.2383, Adjusted R-squared:  0.2157
## F-statistic: 10.57 on 25 and 845 DF,  p-value: < 2.2e-16
```

Supplementary Table 6: Linear regression model of short-term boost in the news, with added "age by manner of death" interaction.

```
##
## Call:
## lm(formula = as.formula(sprintf("perm_boost_relrank ~ %s", predictors)),
##     data = lmdata)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.63192 -0.21951  0.00156  0.23031  0.57993
##
## Coefficients:
##                                  Estimate Std. Error t value Pr(>|t|)
## mean_before_relrank             -0.039227   0.033372  -1.175 0.240153
## age_group70                      0.070331   0.022736   3.093 0.002045 **
## age_group20                      0.096091   0.094853   1.013 0.311325
## age_group30                      0.041532   0.085085   0.488 0.625588
## age_group40                      0.014224   0.048373   0.294 0.768798
## age_group50                     -0.025681   0.034744  -0.739 0.460022
## age_group60                     -0.022031   0.024720  -0.891 0.373062
## age_group80                      0.062061   0.022358   2.776 0.005630 **
## age_group90                      0.112468   0.030095   3.737 0.000199 ***
## death_typeunnatural              0.147611   0.106906   1.381 0.167721
## genderFemale                     0.038463   0.025803   1.491 0.136437
## anglonon_anglo                  -0.113644   0.026591  -4.274 2.14e-05 ***
## anglounknown                    -0.149934   0.030603  -4.899 1.15e-06 ***
## type_groupacademia/engineering  -0.019377   0.070374  -0.275 0.783122
## type_groupgeneral fame          -0.008856   0.044371  -0.200 0.841847
## type_groupknown for death       -0.064415   0.035556  -1.812 0.070396 .
## type_groupleadership            -0.070072   0.029587  -2.368 0.018094 *
```

```
## type_groupsports               -0.044702   0.029831  -1.498 0.134378
## age_group20:death_typeunnatural -0.027778   0.154966  -0.179 0.857782
## age_group30:death_typeunnatural -0.004357   0.151735  -0.029 0.977101
## age_group40:death_typeunnatural  0.026451   0.134728   0.196 0.844400
## age_group50:death_typeunnatural -0.098592   0.127251  -0.775 0.438686
## age_group60:death_typeunnatural  0.059818   0.125787   0.476 0.634521
## age_group80:death_typeunnatural -0.009561   0.193525  -0.049 0.960608
## age_group90:death_typeunnatural -0.288201   0.297859  -0.968 0.333534
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2753 on 845 degrees of freedom
## Multiple R-squared:  0.1189, Adjusted R-squared:  0.09283
## F-statistic: 4.561 on 25 and 845 DF,  p-value: 2.333e-12
```

Supplementary Table 7: Linear regression model of long-term boost in the news, with added "age by manner of death" interaction.

```
##
## Call:
## lm(formula = as.formula(sprintf("peak_mean_boost_relrank ~ %s",
##     predictors)), data = lmdata)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.71524 -0.18611 -0.00282  0.20651  0.61822
##
## Coefficients:
##                                  Estimate Std. Error t value Pr(>|t|)
## mean_before_relrank              0.334205   0.031828  10.500  < 2e-16 ***
## age_group70                     -0.033041   0.021488  -1.538 0.124511
## age_group20                      0.237288   0.089330   2.656 0.008049 **
## age_group30                      0.175763   0.080115   2.194 0.028516 *
## age_group40                      0.035998   0.045584   0.790 0.429916
## age_group50                      0.020332   0.032761   0.621 0.535032
## age_group60                      0.005842   0.023277   0.251 0.801897
## age_group80                     -0.026348   0.021223  -1.241 0.214778
## age_group90                     -0.025258   0.028355  -0.891 0.373308
## death_typeunnatural              0.108666   0.100663   1.079 0.280675
## genderFemale                    -0.007697   0.024242  -0.318 0.750933
## anglonon_anglo                  -0.033544   0.024986  -1.342 0.179797
## anglounknown                    -0.109642   0.029019  -3.778 0.000169 ***
## type_groupacademia/engineering   0.118763   0.066238   1.793 0.073337 .
## type_groupgeneral fame           0.047796   0.041796   1.144 0.253129
## type_groupknown for death       -0.026487   0.033731  -0.785 0.432540
## type_groupleadership             0.026762   0.027648   0.968 0.333343
## type_groupsports                 0.023447   0.028200   0.831 0.405954
## age_group20:death_typeunnatural -0.078726   0.145910  -0.540 0.589650
## age_group30:death_typeunnatural  0.001729   0.142781   0.012 0.990343
## age_group40:death_typeunnatural  0.082247   0.126535   0.650 0.515874
## age_group50:death_typeunnatural -0.030965   0.119968  -0.258 0.796386
## age_group60:death_typeunnatural -0.014870   0.118442  -0.126 0.900118
```

```
## age_group80:death_typeunnatural -0.166931   0.182080  -0.917 0.359509
## age_group90:death_typeunnatural -0.125260   0.280592  -0.446 0.655414
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2591 on 845 degrees of freedom
## Multiple R-squared:  0.2191, Adjusted R-squared:  0.196
## F-statistic: 9.482 on 25 and 845 DF,  p-value: < 2.2e-16
```

Supplementary Table 8: Linear regression model of short-term boost on Twitter, with added "age by manner of death" interaction.

```
##
## Call:
## lm(formula = as.formula(sprintf("perm_boost_relrank ~ %s", predictors)),
##     data = lmdata)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.70715 -0.19327  0.02603  0.21907  0.59020
##
## Coefficients:
##                                  Estimate Std. Error t value Pr(>|t|)
## mean_before_relrank              0.116011   0.033760   3.436 0.000618 ***
## age_group70                      0.038062   0.022793   1.670 0.095301 .
## age_group20                      0.071226   0.094752   0.752 0.452437
## age_group30                      0.179281   0.084978   2.110 0.035174 *
## age_group40                      0.097324   0.048351   2.013 0.044444 *
## age_group50                     -0.009159   0.034750  -0.264 0.792173
## age_group60                     -0.008024   0.024690  -0.325 0.745276
## age_group80                      0.023841   0.022511   1.059 0.289860
## age_group90                      0.007153   0.030076   0.238 0.812081
## death_typeunnatural              0.122294   0.106773   1.145 0.252381
## genderFemale                     0.029356   0.025713   1.142 0.253903
## anglonon_anglo                  -0.034279   0.026503  -1.293 0.196225
## anglounknown                    -0.141044   0.030780  -4.582 5.29e-06 ***
## type_groupacademia/engineering   0.076314   0.070259   1.086 0.277705
## type_groupgeneral fame           0.003185   0.044332   0.072 0.942744
## type_groupknown for death       -0.024310   0.035778  -0.679 0.497031
## type_groupleadership            -0.101816   0.029326  -3.472 0.000543 ***
## type_groupsports                -0.023928   0.029912  -0.800 0.423974
## age_group20:death_typeunnatural  0.090805   0.154766   0.587 0.557546
## age_group30:death_typeunnatural -0.082225   0.151447  -0.543 0.587321
## age_group40:death_typeunnatural -0.019321   0.134215  -0.144 0.885570
## age_group50:death_typeunnatural -0.079483   0.127249  -0.625 0.532389
## age_group60:death_typeunnatural -0.001916   0.125630  -0.015 0.987838
## age_group80:death_typeunnatural -0.006991   0.193131  -0.036 0.971132
## age_group90:death_typeunnatural -0.144877   0.297622  -0.487 0.626539
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2749 on 845 degrees of freedom
```

```
## Multiple R-squared:  0.1214, Adjusted R-squared:  0.0954
## F-statistic:  4.67 on 25 and 845 DF,  p-value: 8.867e-13
```

Supplementary Table 9: Linear regression model of long-term boost on Twitter, with added "age by manner of death" interaction.

Models of news-vs.-Twitter boost difference for fixed person (without interactions)

```
##
## Call:
## lm(formula = as.formula(sprintf("peak_mean_boost_relrank_diff ~ %s",
##     predictors)), data = lmdata)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.6496 -0.1208  0.0038  0.1106  0.7404
##
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    0.007131   0.016294   0.438 0.661761
## mean_before_relrank_diff      -0.077831   0.029007  -2.683 0.007434 **
## age_group20                   -0.177328   0.043731  -4.055 5.47e-05 ***
## age_group30                   -0.091639   0.043024  -2.130 0.033461 *
## age_group40                   -0.112473   0.032340  -3.478 0.000531 ***
## age_group50                   -0.058774   0.025457  -2.309 0.021195 *
## age_group60                   -0.061181   0.021051  -2.906 0.003753 **
## age_group80                    0.012762   0.020081   0.636 0.525260
## age_group90                    0.072718   0.025139   2.893 0.003917 **
## death_typeunnatural            0.132598   0.024312   5.454 6.46e-08 ***
## genderFemale                   0.030131   0.018500   1.629 0.103744
## anglonon_anglo                -0.077795   0.018896  -4.117 4.21e-05 ***
## anglounknown                  -0.017957   0.021921  -0.819 0.412906
## type_groupacademia/engineering -0.026667   0.050811  -0.525 0.599843
## type_groupgeneral fame        -0.011339   0.031869  -0.356 0.722071
## type_groupknown for death      0.028830   0.025684   1.123 0.261965
## type_groupleadership           0.060712   0.021578   2.814 0.005011 **
## type_groupsports               0.004572   0.021517   0.212 0.831794
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1985 on 852 degrees of freedom
## Multiple R-squared:  0.1042, Adjusted R-squared:  0.08629
## F-statistic: 5.827 on 17 and 852 DF,  p-value: 9.067e-13
```

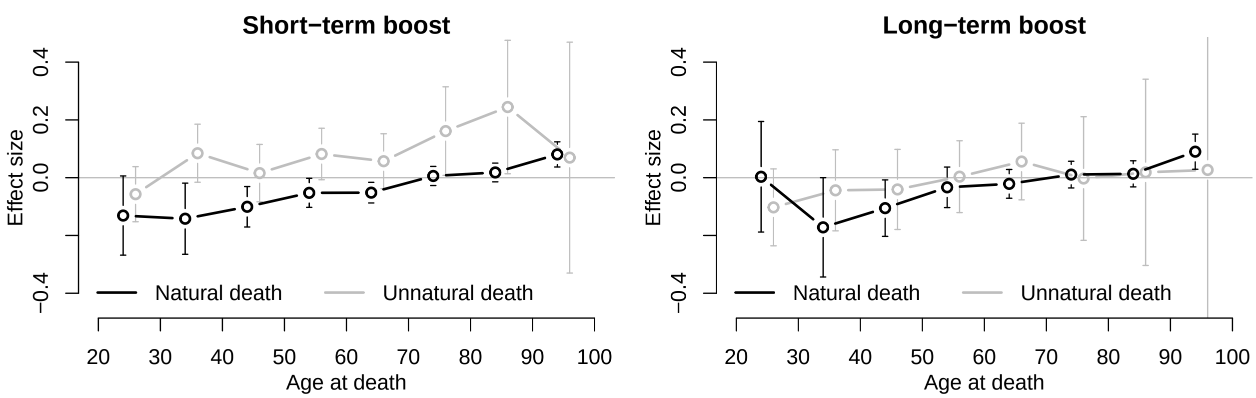
Supplementary Table 10: Linear regression model of news-vs.-Twitter difference in short-term boost.

```
##
## Call:
## lm(formula = as.formula(sprintf("perm_boost_relrank_diff ~ %s",
##     predictors)), data = lmdata)
```

```
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.92186 -0.12959  0.01391  0.14260  0.95349
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                     0.008043   0.022742   0.354  0.72367
## mean_before_relrank_diff       -0.230628   0.040485  -5.697 1.68e-08 ***
## age_group20                    -0.105519   0.061035  -1.729  0.08420 .
## age_group30                    -0.128012   0.060048  -2.132  0.03331 *
## age_group40                    -0.106048   0.045137  -2.349  0.01903 *
## age_group50                    -0.043230   0.035530  -1.217  0.22405
## age_group60                    -0.026262   0.029381  -0.894  0.37165
## age_group80                     0.004226   0.028027   0.151  0.88019
## age_group90                     0.080720   0.035086   2.301  0.02165 *
## death_typeunnatural             0.039642   0.033933   1.168  0.24303
## genderFemale                    0.007763   0.025820   0.301  0.76373
## anglonon_anglo                 -0.074869   0.026373  -2.839  0.00464 **
## anglounknown                    0.023978   0.030594   0.784  0.43341
## type_groupacademia/engineering -0.069726   0.070916  -0.983  0.32578
## type_groupgeneral fame          0.003712   0.044479   0.083  0.93352
## type_groupknown for death       0.001229   0.035846   0.034  0.97266
## type_groupleadership            0.066667   0.030116   2.214  0.02711 *
## type_groupsports                0.008463   0.030031   0.282  0.77816
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2771 on 852 degrees of freedom
## Multiple R-squared:  0.0743, Adjusted R-squared:  0.05583
## F-statistic: 4.023 on 17 and 852 DF,  p-value: 9.057e-08
```

Supplementary Table 11: Linear regression model of news-vs.-Twitter difference in long-term boost.

Models of news-vs.-Twitter boost difference for fixed person (with "age by manner of death" interaction)



Supplementary Figure 9: Dependence of news-vs.-Twitter boost difference (for fixed person) on age at death.

```
##
## Call:
## lm(formula = as.formula(sprintf("peak_mean_boost_relrank_diff ~ %s",
##     predictors)), data = lmdata)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.64846 -0.11978  0.00327  0.10887  0.74189
##
## Coefficients:
##                                  Estimate Std. Error t value Pr(>|t|)
## mean_before_relrank_diff        -0.079660   0.029192  -2.729 0.006487 **
## age_group70                      0.005902   0.016535   0.357 0.721241
## age_group20                     -0.131089   0.068543  -1.913 0.056148 .
## age_group30                     -0.142074   0.061578  -2.307 0.021283 *
## age_group40                     -0.100671   0.035010  -2.876 0.004135 **
## age_group50                     -0.052507   0.025113  -2.091 0.036838 *
## age_group60                     -0.051830   0.017834  -2.906 0.003754 **
## age_group80                      0.018036   0.016191   1.114 0.265611
## age_group90                      0.080562   0.021794   3.696 0.000233 ***
## death_typeunnatural              0.155420   0.077349   2.009 0.044819 *
## genderFemale                     0.032534   0.018614   1.748 0.080860 .
## anglonon_anglo                  -0.076134   0.019147  -3.976  7.6e-05 ***
## anglounknown                    -0.018445   0.022060  -0.836 0.403316
## type_groupacademia/engineering  -0.026851   0.050923  -0.527 0.598128
## type_groupgeneral fame          -0.010738   0.032091  -0.335 0.738007
## type_groupknown for death        0.027646   0.025829   1.070 0.284766
## type_groupleadership             0.060264   0.021657   2.783 0.005512 **
## type_groupsports                 0.004710   0.021646   0.218 0.827786
## age_group20:death_typeunnatural -0.081471   0.112014  -0.727 0.467224
## age_group30:death_typeunnatural  0.071281   0.109837   0.649 0.516537
## age_group40:death_typeunnatural -0.038913   0.097332  -0.400 0.689404
## age_group50:death_typeunnatural -0.020927   0.092143  -0.227 0.820392
## age_group60:death_typeunnatural -0.046500   0.090943  -0.511 0.609270
## age_group80:death_typeunnatural  0.071107   0.139837   0.508 0.611238
## age_group90:death_typeunnatural -0.166528   0.215139  -0.774 0.439120
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1989 on 845 degrees of freedom
## Multiple R-squared:  0.1079, Adjusted R-squared:  0.08154
## F-statistic: 4.089 on 25 and 845 DF,  p-value: 1.466e-10
```

Supplementary Table 12: Linear regression model of news-vs.-Twitter difference in short-term boost, with added "age by manner of death" interaction.

```
##
## Call:
## lm(formula = as.formula(sprintf("perm_boost_relrank_diff ~ %s",
##     predictors)), data = lmdata)
##
## Residuals:
```

```
##      Min       1Q   Median       3Q      Max
## -0.92420 -0.13055  0.01538  0.14045  0.95719
##
## Coefficients:
##                                  Estimate Std. Error t value Pr(>|t|)
## mean_before_relrank_diff        -0.2341465  0.0407524  -5.746 1.28e-08 ***
## age_group70                      0.0106514  0.0230835   0.461  0.64461
## age_group20                      0.0031530  0.0956873   0.033  0.97372
## age_group30                     -0.1718587  0.0859643  -1.999  0.04591 *
## age_group40                     -0.1054249  0.0488746  -2.157  0.03128 *
## age_group50                     -0.0333427  0.0350581  -0.951  0.34184
## age_group60                     -0.0213921  0.0248968  -0.859  0.39046
## age_group80                      0.0133539  0.0226032   0.591  0.55481
## age_group90                      0.0899990  0.0304251   2.958  0.00318 **
## death_typeunnatural             -0.0135298  0.1079812  -0.125  0.90032
## genderFemale                     0.0080192  0.0259857   0.309  0.75770
## anglonon_anglo                  -0.0751648  0.0267296  -2.812  0.00504 **
## anglounknown                     0.0227608  0.0307967   0.739  0.46007
## type_groupacademia/engineering  -0.0697905  0.0710894  -0.982  0.32651
## type_groupgeneral fame           0.0031289  0.0448002   0.070  0.94434
## type_groupknown for death       -0.0002293  0.0360578  -0.006  0.99493
## type_groupleadership             0.0668489  0.0302337   2.211  0.02730 *
## type_groupsports                 0.0050713  0.0302191   0.168  0.86677
## age_group20:death_typeunnatural -0.0923192  0.1563740  -0.590  0.55510
## age_group30:death_typeunnatural  0.1416421  0.1533360   0.924  0.35589
## age_group40:death_typeunnatural  0.0782650  0.1358777   0.576  0.56477
## age_group50:death_typeunnatural  0.0504094  0.1286343   0.392  0.69524
## age_group60:death_typeunnatural  0.0908410  0.1269589   0.716  0.47449
## age_group80:death_typeunnatural  0.0187045  0.1952165   0.096  0.92369
## age_group90:death_typeunnatural -0.0496572  0.3003405  -0.165  0.86872
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2777 on 845 degrees of freedom
## Multiple R-squared:  0.07775,    Adjusted R-squared:  0.05046
## F-statistic: 2.849 on 25 and 845 DF,  p-value: 4.86e-06
```

Supplementary Table 13: Linear regression model of news-vs.-Twitter difference in long-term boost, with added “age by manner of death” interaction.