질병부담계산
DISMOD_mr in GBD 2010

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Contents

Concept of DALY

YLL(Years of Life Lost): 사망으로 인한 손실.

$$\mathrm{YLL} = \mathrm{N} \times \mathrm{L}$$

(N: number of death, L: standard life expectancy at age of death in years)
YLD(Years Lost due to Disability): 장해로 인한 손실

$$\mathrm{YLD} = \mathrm{I} \times \mathrm{DW} \times \mathrm{L}$$

(I: incidence, DW: disability weight, L: average duration of the case until remission or death(years))

- DALY = YLL(years of life lost) + YLD(years lived with disability)

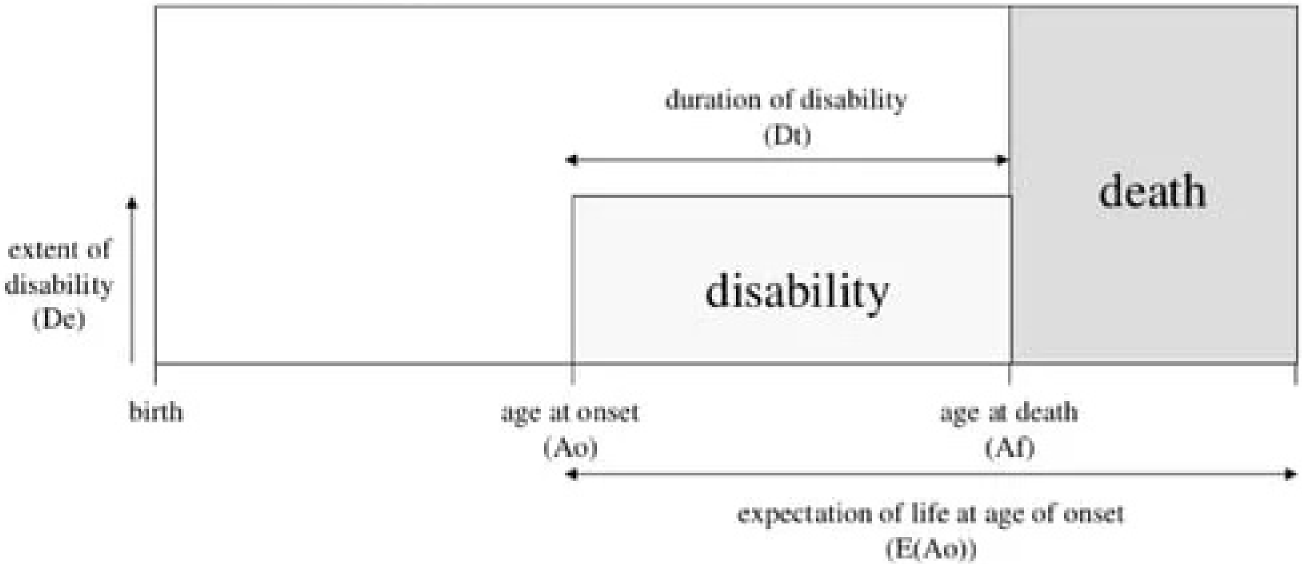


Figure: **Concept of DALY**

사망으로부터 거꾸로 계산: 성균관의대 박재현교수님 강의록

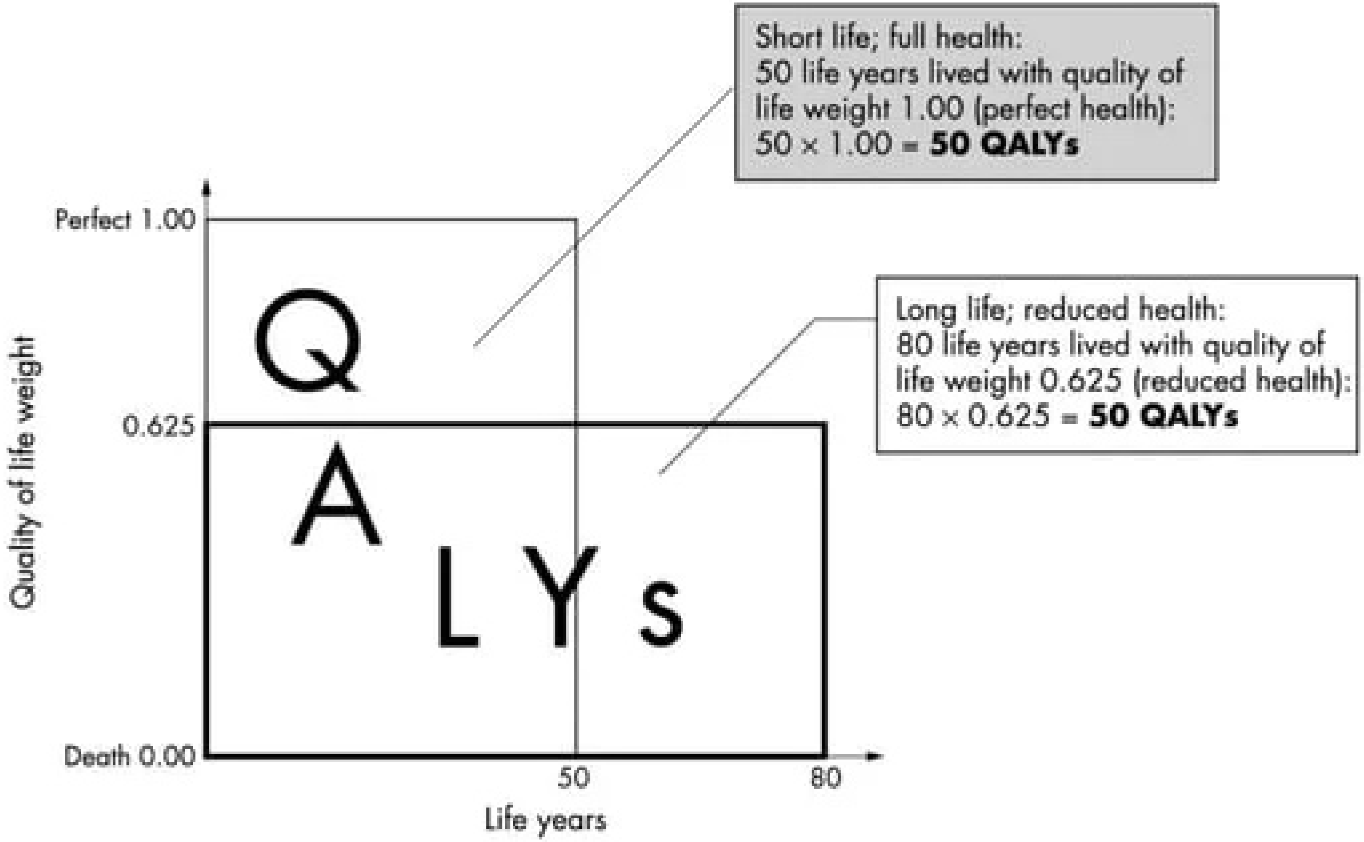


Figure: **Concept of QALY**

태어났을때부터 계산 http://qaly.blog.hu/

Life Expectancy(L)

http://ghdx.healthdata.org/sites/default/files/record-attached-files/IHME_GBD_2010_LIFE_EXPECTANCY_AND_HALE_1970_2010_Y2012M02D23.CSV

Disability Weight(DW)

- **원칙적으로는 person trade off(PTO) 등의 방법을 이용해 survey를 해야..**[4]
- GBD 2010 결과를 그대로 쓴다면..[7]

Articles

Common values in assessing health outcomes from disease and injury: disability weights measurement study for the Global Burden of Disease Study 2010

Joshua A Salomon, Theo Vos, Daniel R Hogan, Michael Gagnon, Mohsen Naghavi, Ali Mokdad, Nazma Begum, Razibuzzaman Shah, Muhammad Karyana, Soewarta Kosen, Mario Reyna Farje, Gilberto Moncada, Arup Dutta, Sunil Sazawal, Andrew Dyer, Jason Seiler, Victor Aboyans*, Lesley Baker*, Amanda Baxter*, Emelia J Benjamin*, Kavi Bhalla*, Aref Bin Abdulhak*, Fiona Blyth*, Rupert Bourne*, Tasanee Braithwaite*, Peter Brooks*, Traolach S Brugha*, Claire Bryan-Hancock*, Rachelle Buchbinder*, Peter Burney*, Bianca Calabria*, Honglei Chen*, Sumeet S Chugh*, Rebecca Cooley*, Michael H Criqui*, Marita Cross*, Kaustubh C Dabhadkar*, Nabila Dahodwala*, Adrian Davis*, Louisa Degenhardt*, Cesar Díaz-Torné*, E Ray Dorsey*, Tim Driscoll*, Karen Edmond*, Alexis Elbaz*, Majid Ezzati*, Valery Feigin*, Cleusa P Ferri*, Abraham D Flaxman*, Louise Flood*, Marlene Fransen*, Kana Fuse*, Belinda J Gabbe*, Richard F Gillum*, Juanita Haagsma*, James E Harrison*, Rasmus Havmoeller*, Roderick J Hay*, Abdullah Hel-Baqui*, Hans W Hoek*, Howard Hoffman*, Emily Hogeland*, Damian Hoy*, Deborah Jarvis*, Jost B Jonas*, Ganesan Karthikeyan*, Lisa Marie Knowlton*, Tim Lathlean*, Janet L Leasher*, Stephen S Lim*, Steven E Lipshultz*, Alan D Lopez*, Rafael Lozano*, Ronan Lyons*, Reza Malekzadeh*, Wagner Marcenes*, Lyn March*, David J Margolis*, Neil McGill*, John McGrath*, George A Mensah*, Ana-Claire Meyer*, Catherine Michaud*, Andrew Moran*, Rintaro Mori*, Michele E Murdoch*, Luigi Naldi*, Charles R Newton*, Rosana Norman*, Saad B Omer*, Richard Osborne*, Neil Pearce*, Fernando Perez-Ruiz*, Norberto Perico*, Konrad Pesudovs*, David Phillips*, Farshad Pourmalek*, Martin Prince*, Jürgen T Rehm*, Guiseppe Remuzzi*, Kathryn Richardson*, Robin Room*, Sukanta Saha*, Uchechukwu Sampson*, Lidia Sanchez-Riera*, Maria Segui-Gomez*, Saeid Shahraz*, Kenji Shibuya*, David Singh*, Karen Sliwa*, Emma Smith*, Isabelle Soerjomataram*, Timothy Steiner*, Wilma A Stolk*, Lars Jacob Stovner*, Christopher Sudfeld*, Hugh R Taylor*, Imad M Tleyjeh*, Marieke J van der Werf*, Wendy L Watson*, David J Weatherall*, Robert Weintraub*, Marc G Weisskopf*, Harvey Whiteford*, James D Wilkinson*, Anthony D Woolf*, Zhi-Jie Zheng*, Christopher J L Murray*

	Estimate (95% uncertainty interval)
Infectious disease	
Infectious disease: acute episode, mild	0·005 (0·002–0·011)
Infectious disease: acute episode, moderate	0·053 (0·033–0·081)
Infectious disease: acute episode, severe	0·210 (0·139–0·298)
Infectious disease: post-acute consequences (fatigue, emotional lability, insomnia)	0·254 (0·170–0·355)
Diarrhoea: mild	0·061 (0·036–0·093)
Diarrhoea: moderate	0·202 (0·133–0·299)
Diarrhoea: severe	0·281 (0·184–0·399)
Epididymo-orchitis	0·097 (0·063–0·137)
Herpes zoster	0·061 (0·039–0·094)
HIV: symptomatic, pre-AIDS	0·221 (0·146–0·310)
HIV/AIDS: receiving antiretroviral treatment	0·053 (0·034–0·079)
AIDS: not receiving antiretroviral treatment	0·547 (0·382–0·715)
Intestinal nematode infections: symptomatic	0·030 (0·016–0·048)
Lymphatic filariasis: symptomatic	0·110 (0·073–0·157)
Ear pain	0·018 (0·009–0·031)
Tuberculosis: without HIV infection	0·331 (0·222–0·450)
Tuberculosis: with HIV infection	0·399 (0·267–0·547)
Cancer	
Cancer: diagnosis and primary therapy	0·294 (0·199–0·411)
Cancer: metastatic	0·484 (0·330–0·643)
Mastectomy	0·038 (0·022–0·059)
Stoma	0·086 (0·055–0·131)
Terminal phase: with medication (for cancers, end-stage kidney or liver disease)	0·508 (0·348–0·670)
Terminal phase, without medication (for cancers, end-stage kidney or liver disease)	0·519 (0·356–0·683)
Cardiovascular and circulatory disease	
Acute myocardial infarction: days 1–2	0·422 (0·284–0·566)
Acute myocardial infarction: days 3–28	0·056 (0·035–0·082)
Angina pectoris: mild	0·037 (0·022–0·058)
Angina pectoris: moderate	0·066 (0·043–0·095)
Angina pectoris: severe	0·167 (0·109–0·234)
Cardiac conduction disorders and cardiac dysrhythmias	0·145 (0·097–0·205)
Claudication	0·016 (0·008–0·028)
Heart failure: mild	0·037 (0·021–0·058)
Heart failure: moderate	0·070 (0·044–0·102)
Heart failure: severe	0·186 (0·128–0·261)
Stroke: long-term consequences, mild	0·021 (0·011–0·037)

	Estimate (95% uncertainty interval)
(Continued from previous column)	
Decompensated cirrhosis of the liver	0·194 (0·127–0·273)
Gastric bleeding	0·323 (0·214–0·461)
Crohn's disease or ulcerative colitis	0·225 (0·152–0·314)
Benign prostatic hypertrophy: symptomatic	0·070 (0·046–0·102)
Urinary incontinence	0·142 (0·094–0·204)
Impotence	0·019 (0·010–0·034)
Infertility: primary	0·011 (0·005–0·021)
Infertility: secondary	0·006 (0·002–0·013)
Chronic respiratory diseases	
Asthma: controlled	0·009 (0·004–0·018)
Asthma: partially controlled	0·027 (0·015–0·045)
Asthma: uncontrolled	0·132 (0·087–0·190)
COPD and other chronic respiratory diseases: mild	0·015 (0·007–0·028)
COPD and other chronic respiratory diseases: moderate	0·192 (0·129–0·271)
COPD and other chronic respiratory diseases: severe	0·383 (0·259–0·528)
Neurological disorders	
Dementia: mild	0·082 (0·055–0·117)
Dementia: moderate	0·346 (0·233–0·475)
Dementia: severe	0·438 (0·299–0·584)
Headache: migraine	0·433 (0·287–0·593)
Headache: tension-type	0·040 (0·025–0·062)
Multiple sclerosis: mild	0·198 (0·137–0·278)
Multiple sclerosis: moderate	0·445 (0·303–0·593)
Multiple sclerosis: severe	0·707 (0·522–0·857)
Epilepsy: treated, seizure free	0·072 (0·047–0·106)
Epilepsy: treated, with recent seizures	0·319 (0·211–0·445)
Epilepsy: untreated	0·420 (0·279–0·572)
Epilepsy: severe	0·657 (0·464–0·827)
Parkinson's disease: mild	0·011 (0·005–0·021)
Parkinson's disease: moderate	0·263 (0·179–0·360)
Parkinson's disease: severe	0·549 (0·383–0·711)
Mental, behavioural, and substance use disorders	
Alcohol use disorder: mild	0·259 (0·176–0·359)
Alcohol use disorder: moderate	0·388 (0·262–0·529)
Alcohol use disorder: severe	0·549 (0·384–0·708)
Fetal alcohol syndrome: mild	0·017 (0·008–0·032)
Fetal alcohol syndrome: moderate	0·057 (0·036–0·087)
Fetal alcohol syndrome: severe	[illegible]

Population-attributable fraction(PAF)[3]

$$\mathrm{PAF} = \frac{\sum_{i=1}^{n} P_i(RR_i - 1)}{\sum_{i=1}^{n} P_i(RR_i - 1) + 1} \text{ : } \textbf{Categorical risk factor}$$

(RR_i: RR for exposure category i, P_i : proportion of the population in exposure category i, n: the number of exposure categories)

$$\mathrm{PAF} = \frac{\int_{x=0}^{m} RR(x)P1(x)dx - \int_{x=0}^{m} RR(x)P2(x)dx}{\int_{x=0}^{m} RR(x)P1(x)dx} \text{ : } \textbf{Continuous}$$

($RR(x)$: RR of a specific disease or injury at exposure level x, $P1(x)$: current (or future) population distribution of exposure, $P2(x)$ counterfactual distribution (ie, TMRED), m maximum exposure level)

Joint effect[5]

$$1 - \mathrm{PAF} = \prod_{r=1}^{R} (1 - \mathrm{PAF}_r)$$

$$\mathrm{PAF} = 1 - \prod_{r=1}^{R} (1 - \mathrm{PAF}_r) : \textbf{Risk factor clusters}$$

Attributable DALY

$$\text{Attributable YLL} = \text{PAF} \times \text{YLL}$$
$$\text{Attributable YLD} = \text{PAF} \times \text{YLD}$$
$$\text{Attributable DALY} = \text{PAF} \times \text{DALY}$$

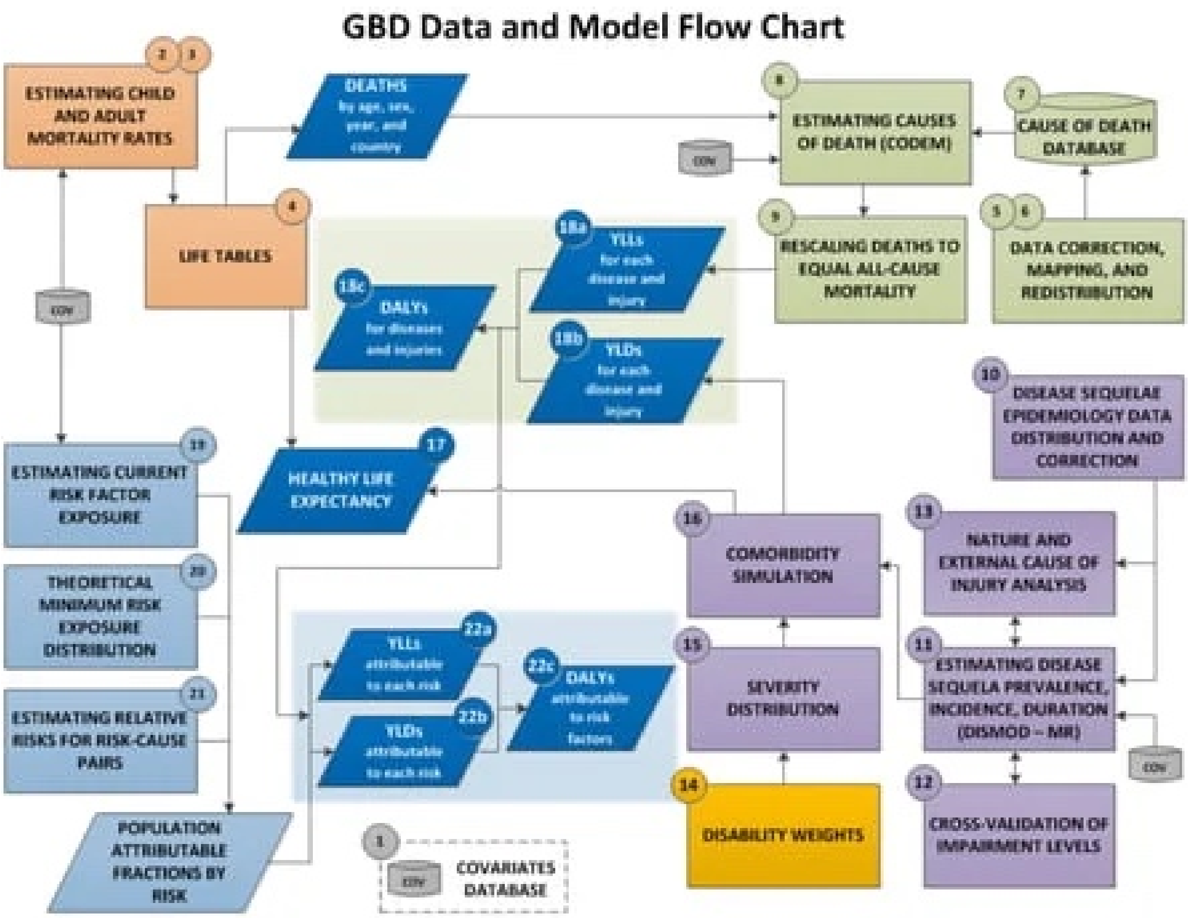
알아야 할것??

DW와 Life expectancy를 가져다 쓴다고 해도.. **연령별, 성별**

- *RR* per risk exposure.
- Prevalence : Risk & disease
- Incidence..
- 사망수(mortality)

즉, 연령별 성별(지역별, 나라별) 다양한 역학지표들이 필요하다!!!!!!!

다 알아도 어렵다..



http://www.slideshare.net/IHME/2-rafael-lozano

Problem

즉, 연령별 성별(지역별, 나라별) 다양한 역학지표들이 필요하다!!!!!!!

- 완벽한 자료는 없다.
- 모르는 부분은 수리적으로 해결해야 한다.

DISMOD(DISease MODelling) 소프트웨어

DISMOD[1]

- GBD 1990
- $i, r, f \rightarrow$ other measure..
- 미분방정식이용

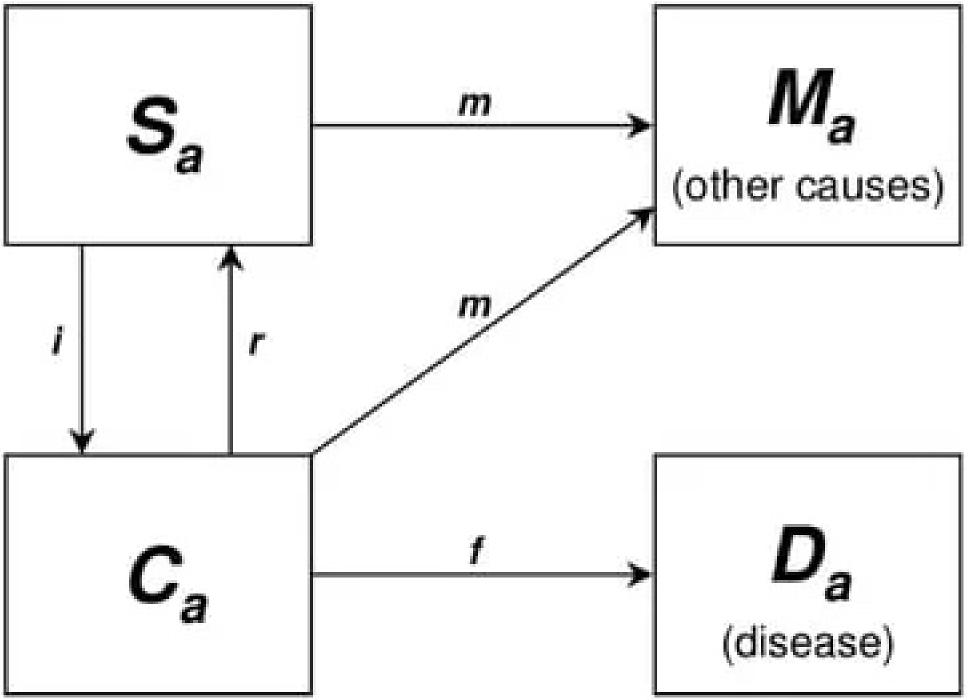


Figure: **Conceptual Disease Model[1]**

(a: age group, S: 건강한 사람의 수, C: 해당 질병상태인 사람의 수, D: 해당 질병으로 죽은 사람의 수, i: incidence, r: remission, f: fatality)

$$\frac{dS_a}{da} = -i_a S_a + r_a C_a \tag{1}$$

$$\frac{dC_a}{da} = -(f_a + r_a) C_a + i_a S_a \tag{2}$$

$$\frac{dD_a}{da} = f_a C_a \tag{3}$$

$$PY_a = \frac{1}{2} \times (S_a + C_a + S_{a+1} + C_{a+1}) \quad (4)$$

$$c_a = \frac{1}{2} \times \frac{C_a + C_{a+1}}{PY_a} \quad (5)$$

$$b_a = \frac{D_{a+1} - D_a}{PY_a} \quad (6)$$

(PY: age interval person-year at risk, c: prevalence, b: mortality)

- m_a: 다른 원인으로 인한 사망률
- $r_a + f_a + m_a$: 질병상태에서 빠져나감
- **Disease duration** 또한 구할 수 있다.

Incidence, remission, case fatality의 세 가지 지표를 토대로 나머지 지표들을 추정하는 소프트웨어가 DISMOD이다.

DISMOD II

- GBD 2000
- 한국논문은 거의 대부분 이것을 이용[9, 6, 10].
- GUI(Graphical User Interface) 지원

Incidence, remission, fatality의 세 지표만 input으로 받았던 한계를 극복

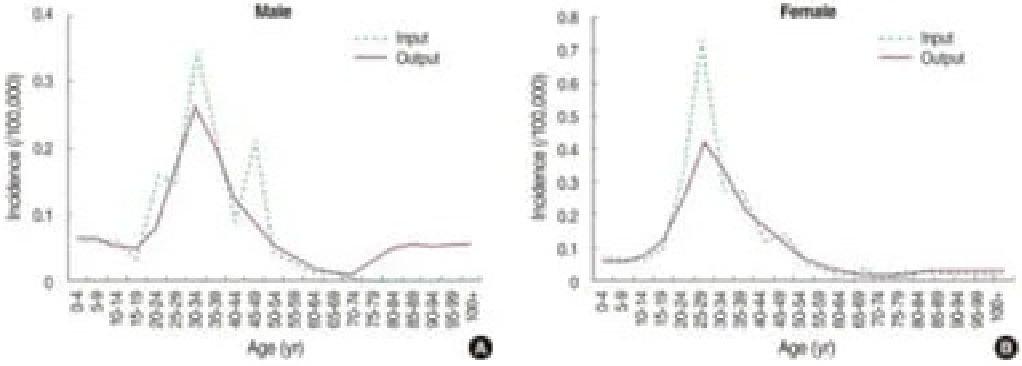
- Prevalence나 mortailty 등으로 역으로 i, f, r들을 추정 가능.
- No exact solution but, 통계적 기법 활용.
- 최소 3종류는 있어야 됨
- Smoothing

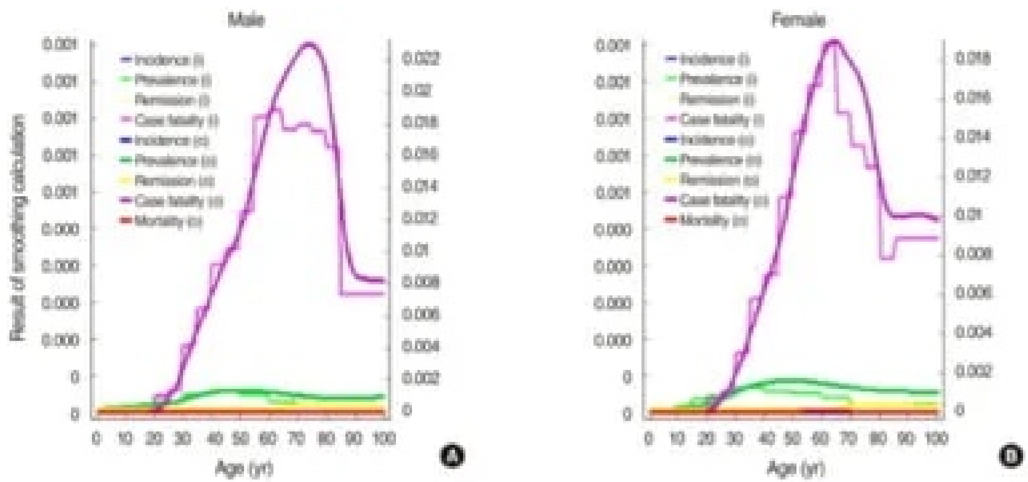
Problem

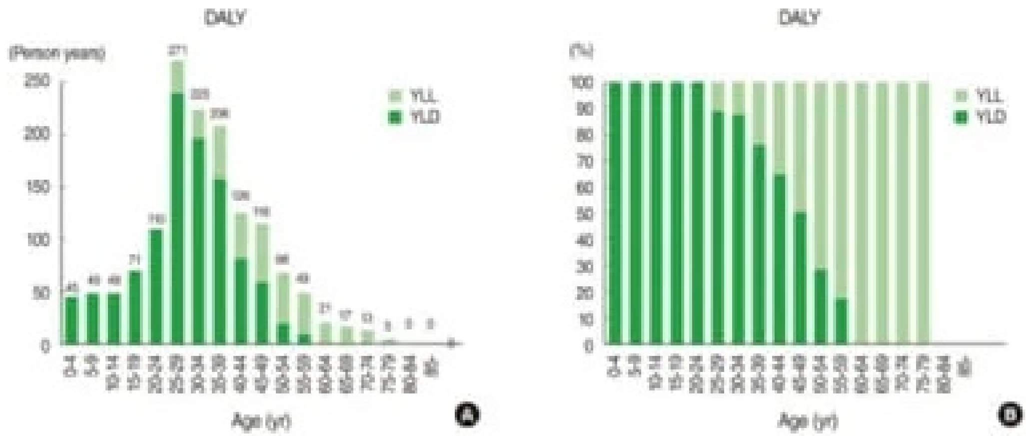
- Global, super-regional, local estimate..
- **Uncertainty**: 숫자 하나로 말하면 땡?? parametric assumption
- 잘 예측하는 것이 목적 $\rightarrow$ 더 flexible한 model필요
- covariate보정??

Meta analysis + Bayesian inference + regression 필요하다.

Example[2]


Male
Input
Output
Incidence (/100,000)
Age (yr)
A
Female
Input
Output
Incidence (/100,000)
Age (yr)
B


Male
Female
Result of smoothing calculation
Age (yr)
A
B


DALY
(Person years)
YLL
YLD
Age (yr)
DALY
(%)
YLL
YLD
Age (yr)

DALY in GBD 2010[3]

Articles

	Men		Women		Both sexes	
	1990	2010	1990	2010	1990	2010
Unimproved water and sanitation	365 244 (18 940–662 551)	171 097 (6841–326 262)	350 629 (17 531–638 433)	166 379 (6690–326 989)	715 873 (36 832–1 279 220)	337 476 (13 150–648 205)
Unimproved water source	147 857 (10 566–282 890)	59 463 (3880–120 764)	140 150 (10 942–271 546)	56 663 (3604–115 704)	288 007 (20 643–553 293)	116 126 (7528–233 136)
Unimproved sanitation	252 779 (8032–480 822)	123 255 (7924–242 588)	244 207 (7348–450 913)	120 851 (3004–242 452)	496 986 (15 380–927 845)	244 106 (6027–478 186)
Air pollution	–	–	–	–	–	–
Ambient particulate matter pollution	1 549 448 (1 345 894–1 752 880)	1 850 428 (1 614 010–2 082 424)	1 360 712 (1 186 992–1 559 747)	1 373 113 (1 187 639–1 563 793)	2 910 161 (2 546 184–3 286 508)	3 223 540 (2 828 854–3 619 148)
Household air pollution from solid fuels	2 253 932 (1 677 785–2 743 681)	1 867 043 (1 359 090–2 452 588)	2 221 558 (1 862 975–2 581 337)	1 611 730 (1 243 526–2 027 067)	4 473 490 (3 663 253–5 266 632)	3 478 773 (2 638 548–4 388 590)
Ambient ozone pollution	77 687 (25 256–134 071)	86 335 (30 551–153 776)	66 224 (22 424–116 663)	66 100 (21 362–115 225)	143 362 (47 539–251 885)	152 434 (52 272–267 431)
Other environmental risks	109 224 (91 805–131 531)	426 280 (343 744–541 465)	100 699 (82 720–119 245)	346 751 (283 555–413 370)	209 923 (177 673–243 565)	773 030 (640 893–929 935)
Residential radon	–	70 014 (9140–154 460)	–	28 978 (4098–64 387)	–	98 992 (13 133–215 237)
Lead exposure	109 224 (91 805–131 531)	356 266 (292 587–435 046)	100 699 (82 720–119 245)	317 772 (265 722–376 431)	209 923 (177 673–243 565)	674 038 (575 858–779 314)
Child and maternal undernutrition	1 805 224 (1 479 043–2 219 888)	719 863 (570 560–909 248)	1 668 365 (1 396 689–1 986 532)	698 442 (569 013–832 012)	3 473 589 (2 906 896–4 175 138)	1 418 305 (1 175 257–1 713 303)
Suboptimal breastfeeding	693 103 (427 028–977 440)	293 449 (175 623–479 772)	581 921 (320 598–814 551)	251 368 (155 884–359 653)	1 275 024 (802 142–1 777 745)	544 817 (338 453–775 077)
Non-exclusive breastfeeding	612 059 (354 736–875 730)	257 771 (143 116–382 459)	505 849 (302 585–720 858)	218 117 (126 383–319 470)	1 117 908 (663 274–1 526 633)	475 888 (277 493–684 427)
Discontinued breastfeeding	81 044 (8643–178 237)	35 678 (3475–79 940)	76 073 (7809–165 395)	33 251 (3090–73 804)	157 117 (16 188–341 702)	68 929 (6445–153 290)
Childhood underweight	1 198 178 (997 627–1 484 105)	458 639 (366 866–561 352)	1 065 774 (898 859–1 299 795)	401 478 (325 516–484 452)	2 263 952 (1 927 356–2 735 871)	860 117 (715 742–1 033 573)
Iron deficiency	39 409 (30 677–47 108)	32 287 (27 925–37 449)	128 675 (92 036–156 884)	87 321 (62 505–107 071)	168 084 (130 444–197 085)	129 608 (93 261–139 985)

Contents

DISMOD_mr

- GBD 2010
- `https://github.com/ihmeuw/dismod_mr`
- 파이썬(python) + MCMC application(c++)
- GBD 2013: DISMOD_ode(only c/c++)

DISMOD II + **Bayesian inference + Bayesian meta-regression**[8]

3줄요약

수식은 무조건 싫다면 밑의 개념만..

1. **Bayesian** : Parametric assumption, expert prior → **flexible model**
   - 예: Local fit 수행 시 global fit을 prior로: **cascade**
   - Prevalence: negative binomial distribution, RR: log-normal
   - MCMC로 uncertainty 추정가능
2. **Meta** : Global, Super-regional, regional fit using meta-analysis.
3. **Regression**: covariate보정
   - 예: 나이, 진단방법의 차이 등..

Introduction to bayesian inference

ThinkBayes 슬라이드 참조

Prevalence formula[8]

$$
\begin{aligned}
\mathbf{p}(p_i \mid \pi_i, \delta_i, n_i) &\propto \frac{\Gamma(\lfloor p_i n_i \rfloor + \delta_i)}{\Gamma(\delta_i)} \left(\frac{\delta_i}{\pi_i + \delta_i}\right)^{\delta}_{i} \left(\frac{\pi_i}{\pi_i + \delta_i}\right)^{\lfloor p_i n_i \rfloor} \\
\pi_i &= \int_{a=a_{si}}^{a_{ei}} \boldsymbol{\pi}(a) e^{\alpha U_i + \beta X_i + \beta' X_i'} \mathbf{d}w_i(a) \\
\alpha_j &\sim \text{Normal}\left(0, \sigma_{\ell(j)}^2\right) \\
\delta_i &= e^{\eta + \zeta Z_i}
\end{aligned}
$$

Where p_i is the prevalence of observation i; π_i is the expected value of this prevalence, δ_i is the dispersion, and n_i is the effective sample size of the observation. Γ denotes the gamma function, $\boldsymbol{\pi}$(a) is the age-specific piecewise linear spline (defined below), α is a vector of random effects, β and β' are vectors of fixed effects, U_i is a row of the random effect design matrix, X_i and X_i' are rows from the fixed effect country-prediction and cross-walk design matrices, and w_i(a) is the age-specific population weight structure. σ_l is the standard deviation for random effects at level l of the spatial hierarchy, and $l(j)$ is the level of random effect j. η is the log of the negative binomial dispersion parameter at the reference level, ζ is the generalised negative binomial fixed effect vector and Z_i is a row from the corresponding design matrix.

The age-specific piecewise linear spline $\boldsymbol{\pi}$(a) has a set of model-specific knots $\{a_1, \ldots, a_K\}$ and is defined by the equation:

K

파헤쳐보면..

Generalized negative binomial distribution

- Rate때 많이 쓰는 poisson assumption은 parameter가 1개(λ: 평균=분산)
- parameter 2개로 확장 $\rightarrow$ flexible: quasi-poisson, gamma, **neg-bin**

$\pi(a)$: **age-specific piecewise linear spline**

- Age 구간 몇개로 쪼갠 후 구간 내에서 linear
- ex: 0,20,40,80,100 $\rightarrow$ 4개 구간에서.. + smoothing

X_i, X_i': **fixed effect**

- 일반적인 fixed effect & case definition 차이..

U_i: **random effect**: Global, Asia, Korea..

n_i: **effective population size, 이거없으면** p_i**의 s.e라도 있어야..**

Expert prior

Smoothness

- Slightly, moderately···

Age pattern

- 사전에 알고 있는 지식을 prior로...
- Ex: chronic disease- Age에 따라 증가한다.

Heterogeneity

- Dispersion parameter
- $\delta_i = \exp(\eta + \xi Z_i)$
- Slightly, moderately...

Zero remission assumption

- 완치가능? 재발?

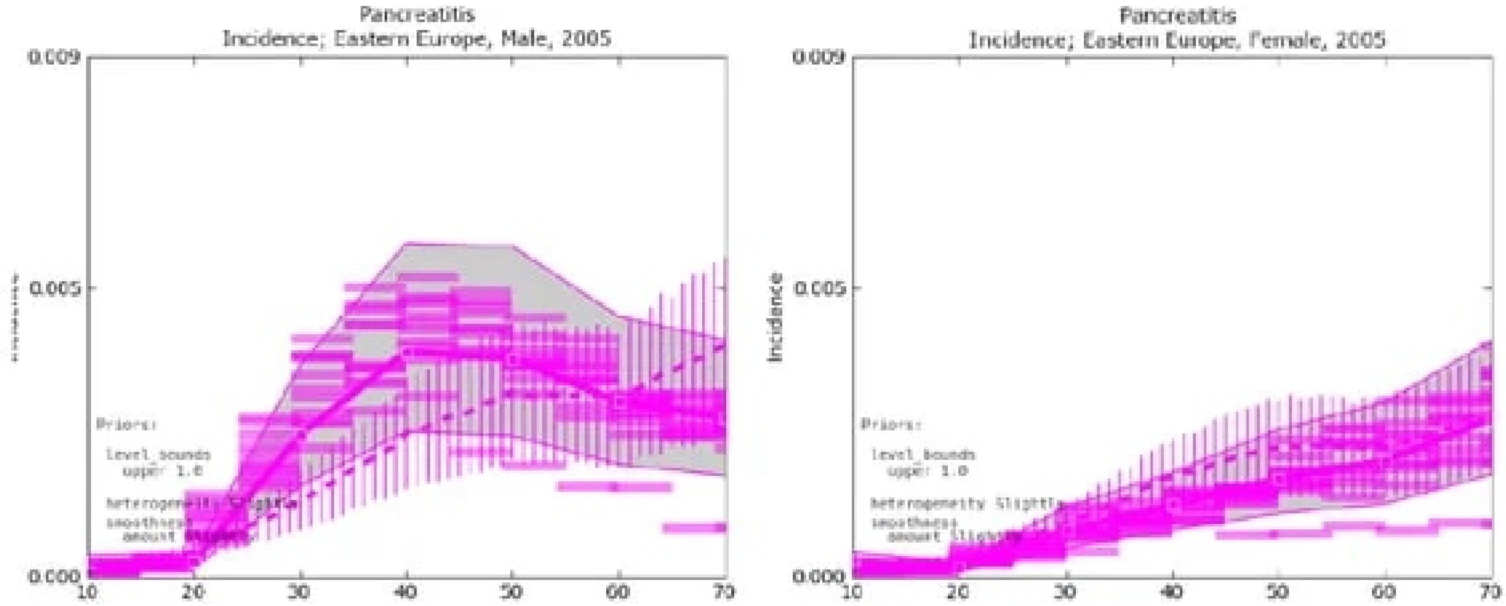
Range: 0~1($p, i, r, f \ldots$), else(RR, $smr \ldots$)

Summary: DISMOD_mr

1. DISMOD I, II : parameter들 사이의 관계 - **미분방정식**이용
2. **Expert prior** + **neg-bin** : **Posterior inference**
3. Estimate **uncertainty**
4. Meta-regression : **Covariate** + **Multi-level**(region)

Example[8]

Web Figure 2: Empirical prior and posterior estimates for pancreatitis in Eastern Europe, 2005. Dashed line with horizontal bars shows the mean and standard deviation of the empirical priors (with identical age pattern for sexes). Solid line with grey shaded region shows the mean and 95% UI of the posterior distribution. The empirical Bayes approach to hierarchical modeling permits estimation of differing age patterns in the face of differing data.



주의점: Posterior inference

계산한 p값 등은 평균, 표준편차 형태로 나오지 않는다

- 앞서 나온 확률분포에서 샘플링 $\rightarrow$ **1000개의 후보값?**
- 1000개라면 알아서 mean 또는 median, 5% percentile 찾아서 쓴다.
- $p \times RR$ 의 uncertainty를 구한다면 **1000개** $\times$ **1000개의 경우의 수**를 다 곱해보고 그것을 기반으로 uncertainty계산하는 것이 원칙.

Example: `https://www.dropbox.com/s/ifm5og0o8jhctgv/United%20States%20of%20America-male-2010_20140711.csv?dl=0`

책추천

1. **NECA 연구방법시리즈 3. 베이지안 메타분석법**
2. 개발자의 책 but 미완성..
   `https://www.dropbox.com/s/x6r4lb7q2jmw831/book.pdf?dl=0`
3. Bayesian Data Analysis(BDA) 3rd edition by Andrew Gelman: 베이지안통계의 교과서
4. 파이썬 라이브러리를 활용한 데이터 분석 by Wes Mckinney: 한글번역판 존재

Contents

1. Introduction
   - DALY, attributable DALY
   - DISMOD, DISMOD II
2. DISMOD_mr: Bayesian meta-regression
   - Introduction to bayesian approach
   - Bayesian meta-regression in Dismod_mr
3. **Practice**
   - Install Dismod_mr
   - Data format
   - Developer's example: Parkinson's disease
   - Kim's example: Age-specific RR
4. Conclusion

실습에 들어가기 전에...

- 설치가 매우 어렵다 → **윈도우에서 설치불가!!!!**
- 돌리기도 어렵다: 파이썬 기초 + 데이터분석을 위한 파이썬 패키지..
- Open source 임을 감안해도 **설명이 매우 부족**.
- 개발팀(IHME)이 자신들 외에 다른 팀이 이용할 것을 전혀 고려하지 않음. **데이터를 보내주면 돌려주겠다는 마인드**...
- GBD 2013의 DISMOD_ode는 c++ 커맨드라인으로만 실행.
- Cascade: IHME member외에 접근 불가.

Web site

- **Institute for Health Metrics and Evaluation**: `http://www.healthdata.org/`
- **Github page of DISMOD_mr**: `https://github.com/ihmeuw/dismod_mr`

설치

어렵다.. & Macbook/Linux에서만 가능.

- 가상머신으로 설치된 우분투리눅스 불러오기
- 가상머신: **Oracle VM VirtualBox**
  `https://www.virtualbox.org/wiki/Downloads`
- 우분투리눅스: **발표자 자체 제작**
  - `http://me2.do/xBy86tQC` & `http://me2.do/5iUu62xT`
  - 파일 2개 다운받아서 7z파일 압축푼다(반디집이용) or 제공되는 usb 이용.

VM VirtualBox 다운로드

가상머신 불러오기

1. VirtualBox 실행 → 파일 → 가상 시스템 가져오기 → 압축푼 파일 지정.
2. dismodmr_jskim_32bit 클릭 → 설정 → 메모리 및 비디오메모리 넉넉하게.
3. dismodmr_jskim_32bit 더블클릭 → 비번: **dismodmr**

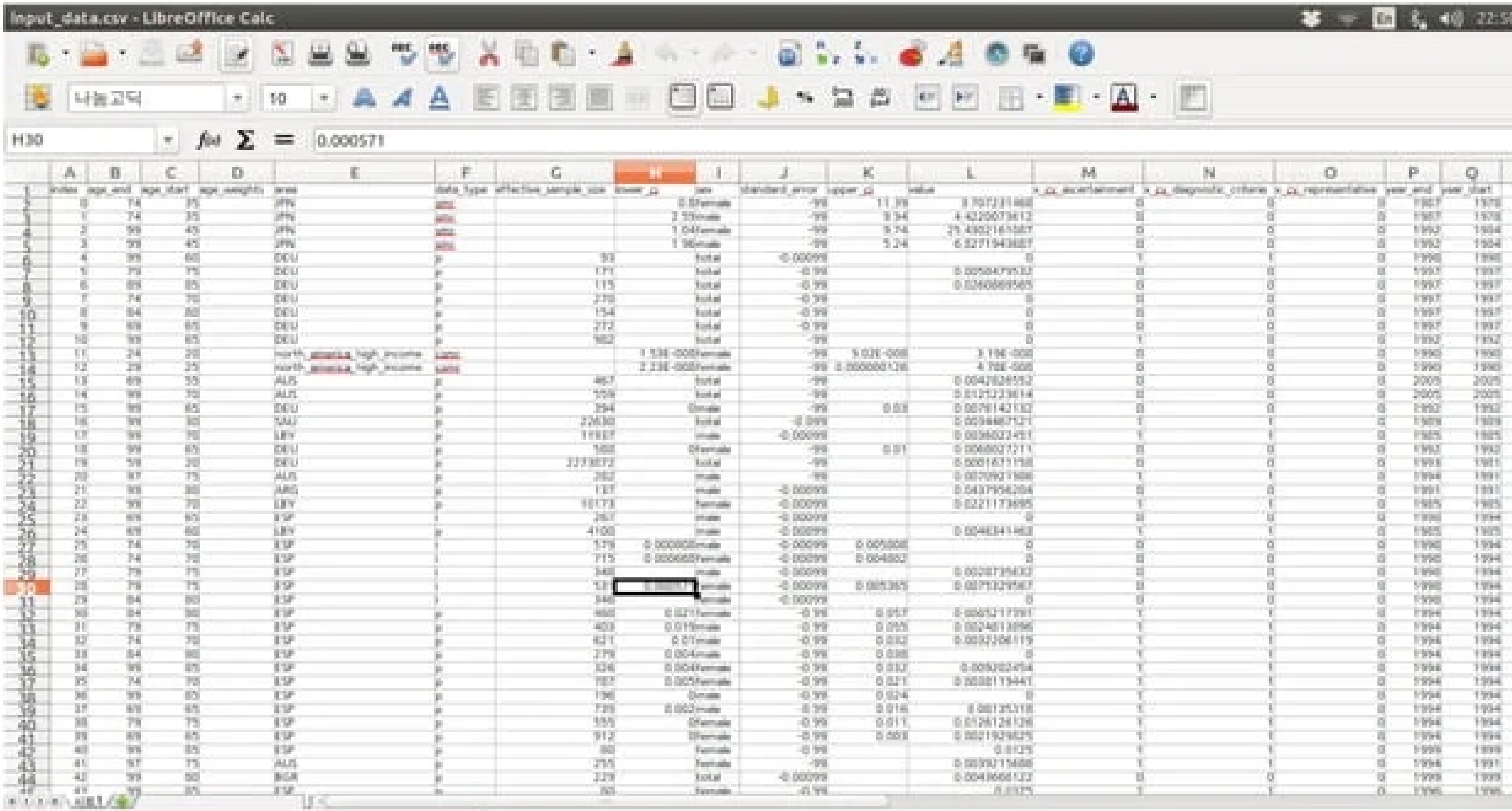
Example data

가상머신에서

1. 왼쪽 두번째 위에 있는 아이콘(Files) 클릭
2. dismod_mr-master 폴더 더블클릭
3. examples 폴더 더블클릭
4. pd_sim_data 폴더 더블클릭

Input file

input_data.csv 더블클릭



주의점

data_type: $p, i, f, r, smr, csmr, rr$ & **value**: 값

1. Effective population size가 있거나
2. standard_error가 있거나
3. lower_ci, upper_ci가 있거나.. 셋 중 최소 하나는 있어야 한다.

Why?

- **p 숫자 딸랑 하나만 가지고는 uncertainty interval계산이 안된다.**
- Meta-analysis에서 weight에 해당하는 부분.

Expert prior

parameters.json: 지표 별로 prior information 지정 & age그룹지정은 따로 (age)

- **increasing** or **decreasing**: 나이에 따라 증가하는가? age_start, age_end
- level_bounds: 범위(ex: upper 1, lower 0)
- level_value: 미리 값 지정(ex: zero remission-age_after=age_before=100, value=0)
- parameter_age_mesh: Piecewise linear spline에서 knot- 촘촘할수록 변화가 크다.
- heterogeneity: Slightly, Moderately, Very
- smoothness: age_start, age_end, amount: Slightly, Moderately, Very
- fixed effect, random effect

Others: 건들지 말것

Regional information: 한국은 **KOR**

- hierarchy.json
- nodes_to_fit.json

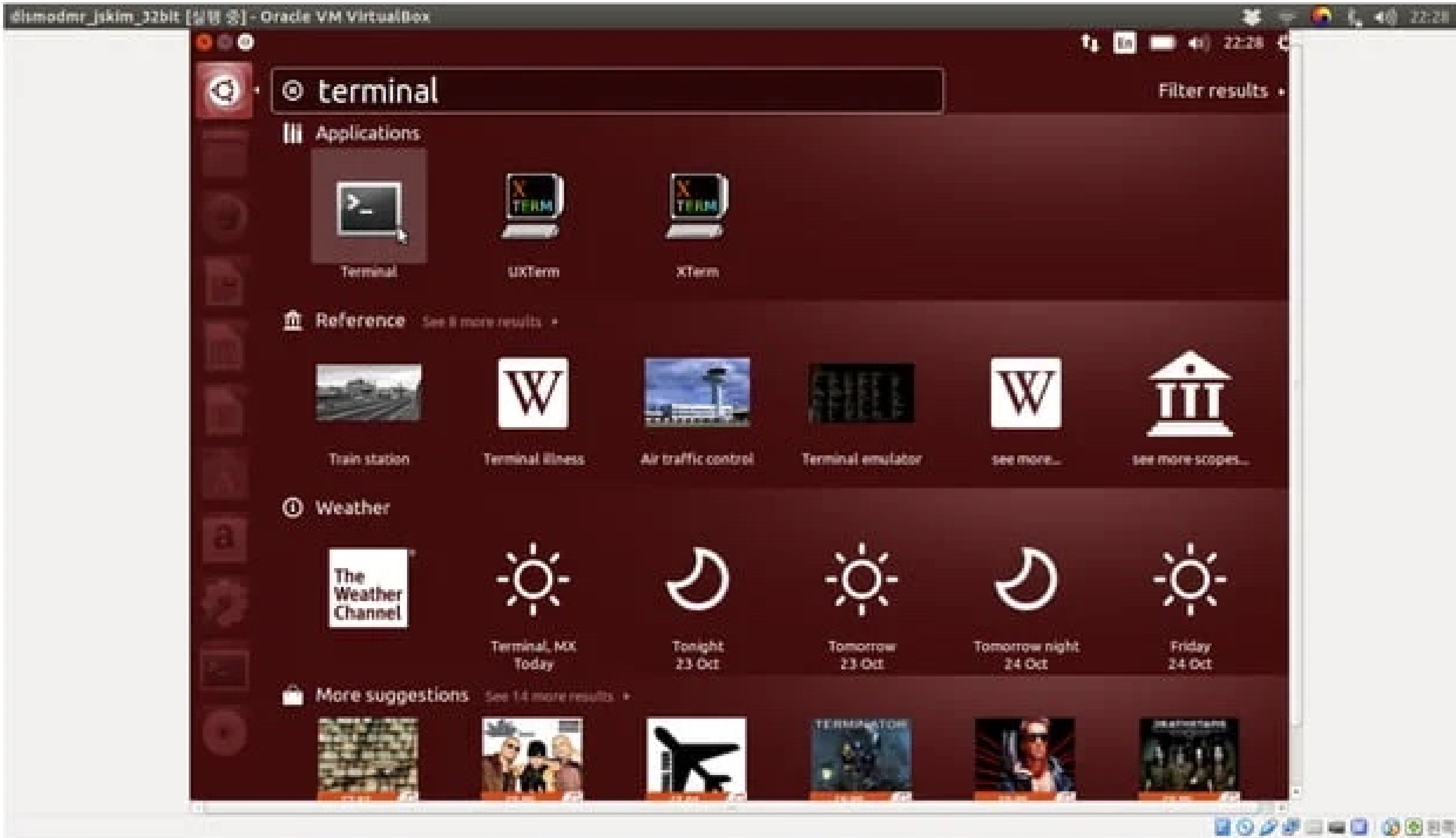
Output format

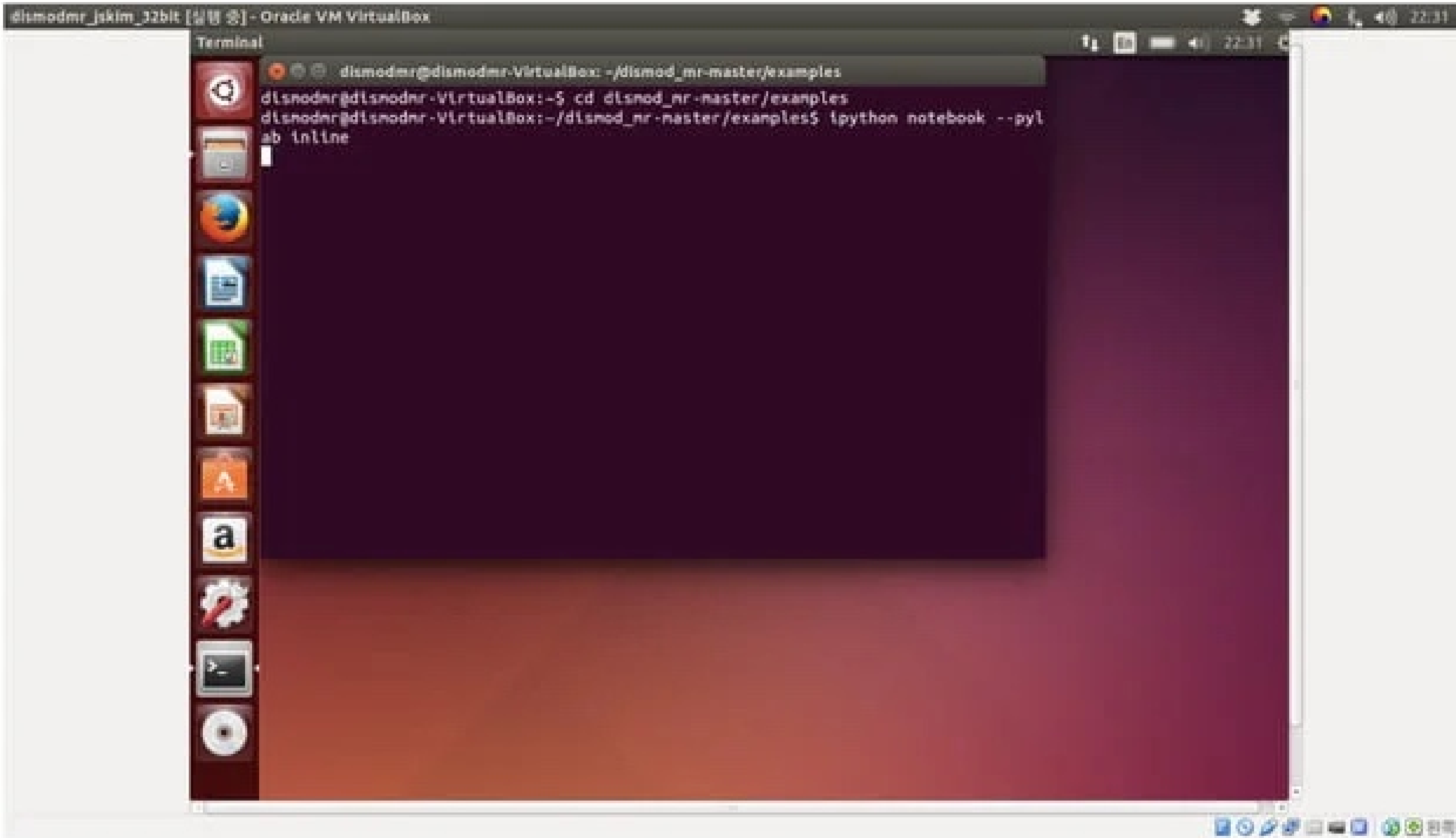
- output_template.csv

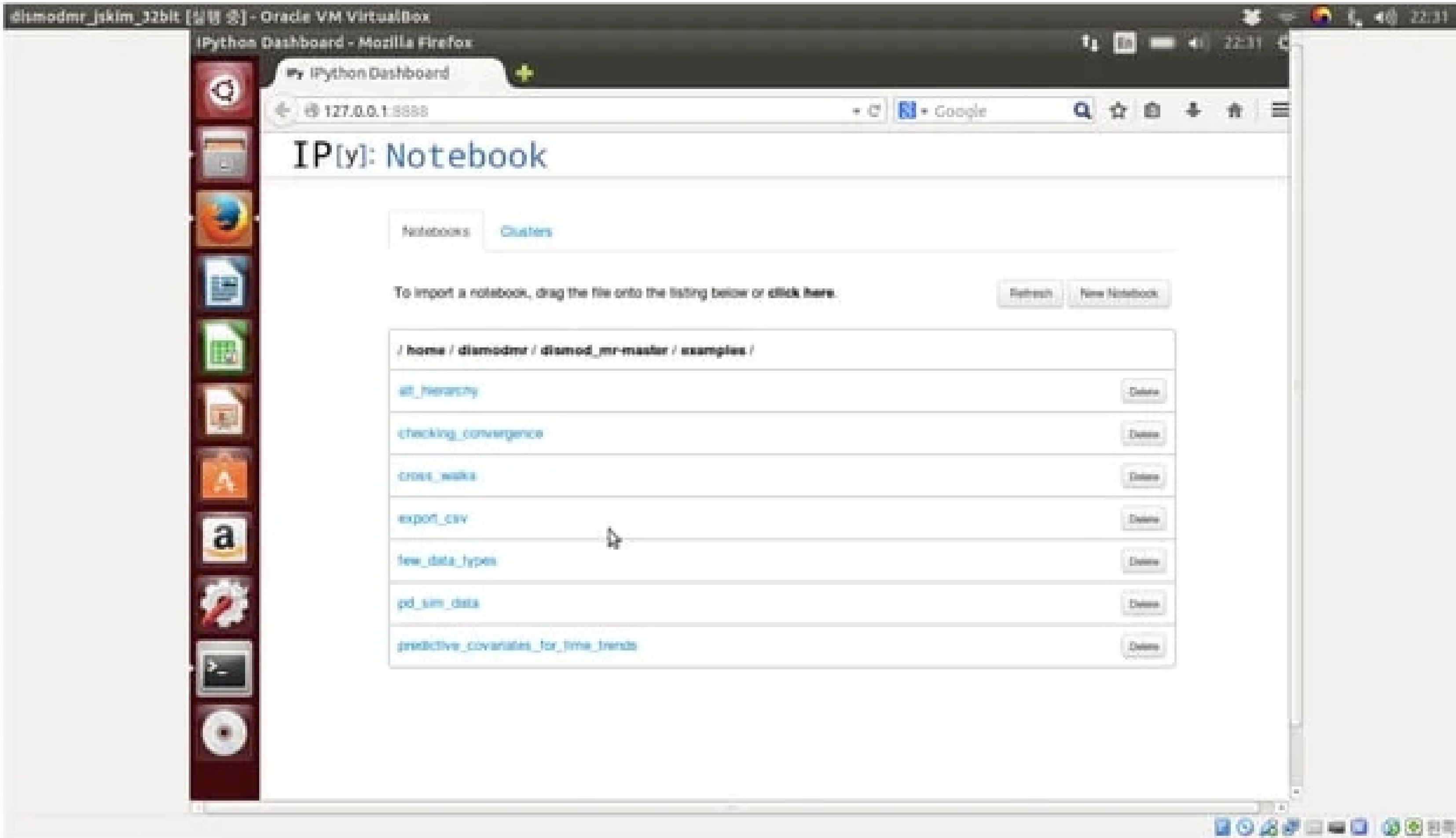
Developer's example: Parkinson's disease

실행방법

1. 바탕화면에서 맨 왼쪽 위 아이콘(소용돌이모양) 클릭
2. 검색창에 **terminal** 입력
3. **terminal** 실행
4. **cd dismod_mr-master/examples** 입력 후 엔터
5. **ipython notebook –pylab inline** 입력 후 엔터(선 2개임)


dismodmr_jskim_32bit - Oracle VM VirtualBox
22:28
terminal
Filter results
Applications
Terminal
UXTerm
XTerm
Reference
Train station
Terminal illness
Air traffic control
Terminal emulator
see more...
see more scopes...
Weather
The Weather Channel
Terminal, MX
Today
Tonight
23 Oct
Tomorrow
23 Oct
Tomorrow night
24 Oct
Friday
24 Oct
More suggestions


Oracle VM VirtualBox
Terminal
dismodmr@dismodmr-VirtualBox: ~/dismod_mr-master/examples
dismodmr@dismodmr-VirtualBox:~$ cd dismod_mr-master/examples
dismodmr@dismodmr-VirtualBox:~/dismod_mr-master/examples$ ipython notebook --pylab inline


dismodmr_jskim_32bit - Oracle VM VirtualBox
IPython Dashboard - Mozilla Firefox
IPython Dashboard
127.0.0.1:8888
Google
IP[y]: Notebook
Notebooks
Clusters
To import a notebook, drag the file onto the listing below or click here.
Refresh
New Notebook
/ home / dismodmr / dismod_mr-master / examples /
alt_hierarchy
checking_convergence
cross_walks
export_csv
few_data_types
pd_sim_data
predictive_covariates_for_time_trends
Delete

발표자 example: 핸드폰 사용과 cancer

여러 논문에서 **age범위**, **RR값과 CI(or s.e)**, year들로 데이터를 만들고 meta-regression

- Age-specific RR

Contents

- GBD 2013에서는 DISMOD_ode(DISMOD_mr 2.0)를 이용하여 계산속도가 비약적으로 향상됨.
- 따라서 cascade 가능(global fit이 super-regional의 prior, super-regional fit이 reginal의 prior)
- DISMOD_mr 설치 및 실행이 매우 어렵다. **전문가 고용** or **IHME에 데이터 바쳐야**. . .
- 최신 Methodology 융합의 결정판 - 종합예술, **GBDology???**

Summary

$$\text{Bayesian} = \text{Uncertainty(neg.bin)} + \text{Expert prior}$$
$$\text{Bayesian meta-regression} = \text{Bayesian} + \text{Meta-regression}$$
$$\text{DISMOD\_mr} = \text{Diff.eq} + \text{Bayesian meta-regression}$$

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