## 2025

jinha

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2025 PDC .

flyinyou@gmail.com

2 1.

2.1

# 3 2.

3.1  $(: \quad , \quad , \quad )$ (: (Gradient) (Bradford Hill) (Biological Gradient)' 1. Strength of association Consistency Specificity Temporality Dose-response Plausibility  ${\bf Coherence}$ Experiment Analogy

3.2

.

• (Linear Relationship): , , , 2 2 .

 $\bullet \qquad \hbox{(Non-linear Relationships):} \qquad - \qquad .$ 

```
( )
        (Threshold Effects):
        (Saturation Effects):
  • U J
               (U-shaped or J-shaped Relationships): U
       . J
                                              U
                 . , U , J
 2
(Linear)
                                              ( )
             ( )
(Threshold)
(Saturation)
Ù
                                                                          A
(U-
shaped)
J
(J-
shaped)
```

## 4 3.

4.1	: ,				
,	(Exposure) (Absorption),	(Distribution),		(Elimination)	, , (dose) (ADME)
-		,			, , , ,
	- ,	, , (	biomarker)	, , ,	
				٠	
4.2	:				
right)"	(Gaussi	an distribution)	,	ш	(skewed to the
	, ,	. ,	(mixed mode	els)	(:
4.3	:				
	nt Censoring) . on-informative)'	,	' (Censoring)' (: )	. (Survi , , Kaplan-Meio	
	. ,	,			,
•	:	,		·	
_	•				

```
(Competing Risks)'
             , Kaplan-Meier
      (Cumulative Incidence Function, CIF)
                                                    (cause-specific hazard function),
(subdistribution hazard function)
                                        (Information Bias) ,
                                                                    (Detection Bias)'
 .18
                (Healthy Worker Effect)'
                                                (Selection Bias)
                                                                        .3
                        .18
   .18
       (Ascertainment Bias)' '
                                 (Sampling Bias)'
.14
                            (SMR)
                                                  .18
                                                  (Effect Modification)'
                                                                              .20
       3
                              .21
                                    (Confounding)
                                                               3
                                                               (Precision Epidemiology)'
                (product terms)
                                                 (stratification)
                               (Odds Ratio, OR)
                                                                             OR
(Relative Risk, RR)
                                                   (Biological Plausibility)
```

9

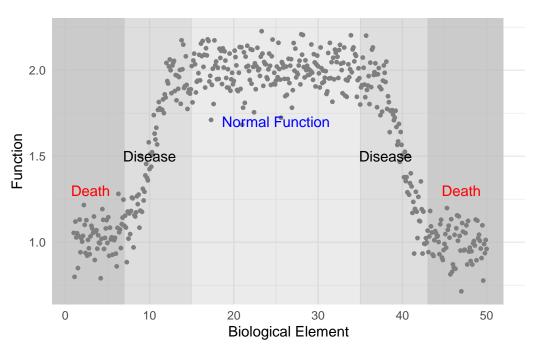
## 5.1 Exposure (Dose) and Health

```
if(!require(tidyverse)) install.packages("tidyverse")
if(!require(ggplot2)) install.packages("ggplot2")
if(!require(knitr)) install.packages("knitr")
if(!require(kableExtra)) install.packages("kableExtra")
```

,

```
basic %>%
  ggplot(aes(x= trace.e, y = hstatus)) +
  scale_x_continuous(name="Biological Element") +
  scale_y_continuous(name="Function") +
  theme_minimal()+
```

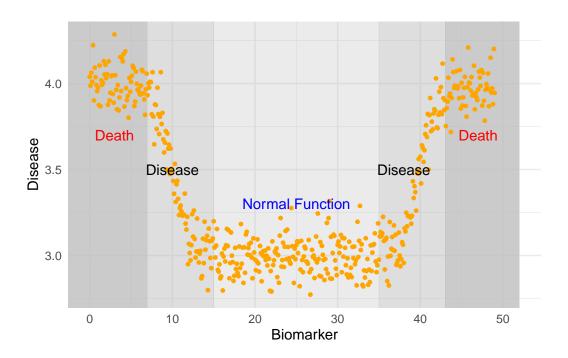
```
geom_rect(data=basic[1,],aes(xmin=-Inf, xmax=7, ymin=-Inf, ymax=Inf), fill= 'grey', alpha:
geom_rect(data=basic[1,],aes(xmin=7, xmax=15, ymin=-Inf, ymax=Inf), fill= 'grey', alpha:
geom_rect(data=basic[1,],aes(xmin=15, xmax=35, ymin=-Inf, ymax=Inf), fill= 'grey', alpha:
geom_rect(data=basic[1,],aes(xmin=35, xmax=43, ymin=-Inf, ymax=Inf), fill= 'grey', alpha:
geom_rect(data=basic[1,],aes(xmin=43, xmax=52, ymin=-Inf, ymax=Inf), fill= 'grey', alpha:
geom_point(size=1, color = 'grey50') +
annotate(geom="text", x=c(3,47), y=c(1.3, 1.3), label="Death", color="red") +
annotate(geom="text", x=c(10,38), y=c(1.5, 1.5), label="Disease", color="black") +
annotate(geom="text", x=25, y=1.7, label="Normal Function",color="blue")
```



Y . . . .

#### 5.2 1:

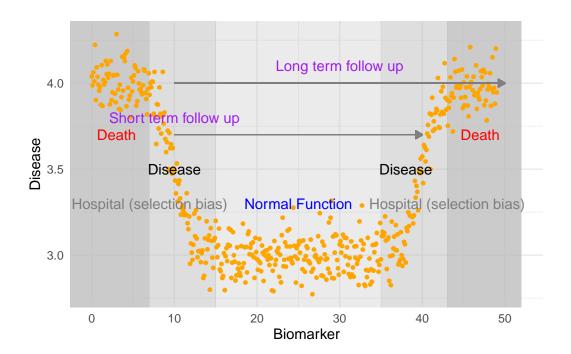
```
theme_minimal()+
  scale_x_continuous(name="Biomarker") +
 scale_y_continuous(name="Disease") +
 geom_rect(data=basic[1,],aes(xmin=-Inf, xmax=7, ymin=-Inf, ymax=Inf), fill= 'grey', alpha
 geom_rect(data=basic[1,],aes(xmin=7,
                                         xmax=15, ymin=-Inf, ymax=Inf), fill= 'grey', alpha
 geom_rect(data=basic[1,],aes(xmin=15,
                                         xmax=35, ymin=-Inf, ymax=Inf), fill= 'grey', alpha
 geom_rect(data=basic[1,],aes(xmin=35,
                                         xmax=43, ymin=-Inf, ymax=Inf), fill= 'grey', alpha
                                         xmax=52, ymin=-Inf, ymax=Inf), fill= 'grey', alpha
 geom_rect(data=basic[1,],aes(xmin=43,
 geom_point(size=1, color = 'orange') +
  annotate(geom="text", x=c(3,47), y=c(3.7, 3.7), label="Death",
                                                                  color="red") +
 annotate(geom="text", x=c(10,38), y=c(3.5, 3.5), label="Disease", color="black") +
                                                 label="Normal Function",color="blue")
  annotate(geom="text", x=25,
                                   y=3.3,
fig1
```



### 5.3 (community base cohort study)

. U-shap J-shap

J-shap



, short-term follow up long term follow up . short-term follow up U-shap , long term follow up J-shap . .

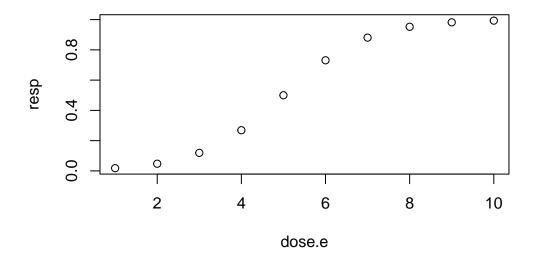
## 5.4 : sigmoid curve vs linear regression

dose.e	resp
1	0.0179862
2	0.0474259
3	0.1192029
4	0.2689414
5	0.5000000
6	0.7310586
7	0.8807971
8	0.9525741
9	0.9820138
10	0.9933071

```
sigmoid.f = function(x){
   1/(1+exp(5-x))
}

df = tibble(
   dose.e = c(1:10),
   resp = sigmoid.f(dose.e)
)
   df %>% kbl() %>%
    kable_paper("hover", full_width = F)
```

```
plot(df)
```



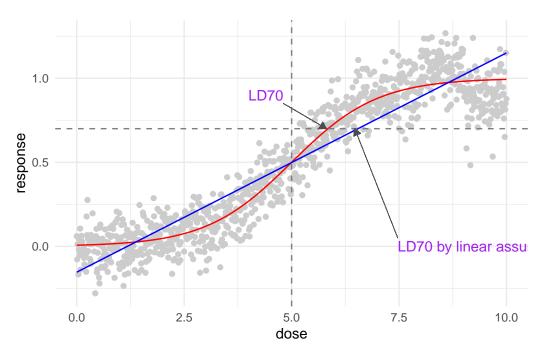
LD50 , LD70 .

#### [1] 5.81

```
mod1<-glm(resp ~ poly(x, 1))
pred1<-predict(mod1)
ld70.lm = x[which(pred1 >0.69 & pred1 <0.71)] %>% min(.)
ld70.lm
```

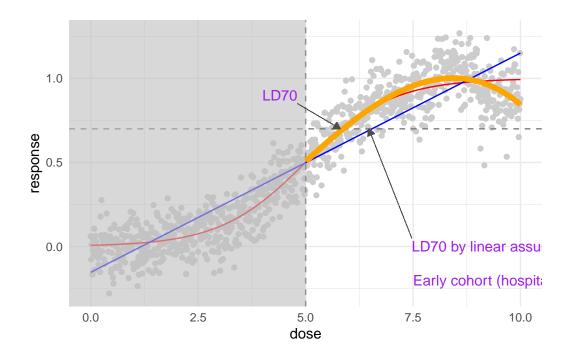
#### [1] 6.47

```
df = tibble(dose = x, response= resp)
df %>%
    ggplot(aes(x=dose, y=response)) +
```



5.5

```
early_cohort = df %>% filter(dose > 5)
df %>%
 ggplot(aes(x=dose, y=response)) +
  geom_point(color = 'grey80') + theme_minimal()+
 geom_line(aes(y= sigmoid.f(dose)), color ='red') +
  geom_line(aes(y= predict(lm(response ~ dose))), color ='blue') +
 geom_vline(xintercept = 5, linetype=2, color='grey50') +
 geom_hline(yintercept = 0.7, linetype=2, color='grey50') +
 annotate(geom="text", x=c(7.5), y=c(-0.2),
           label="Early cohort (hospital base)", color="purple", hjust=0) +
  geom_rect(data=df[1,],aes(xmin=-Inf,
                                       xmax=5, ymin=-Inf, ymax=Inf),
           fill= 'grey', alpha=0.6) +
  geom_line(data= early_cohort,
              aes(y= predict(lm(response ~ poly(dose,3)))), color ='orange', size = 2) +
   annotate(geom="text", x=ld70.sm -1, y=0.9, label="LD70",
           color="purple", hjust=1) +
  geom_segment(aes(x=ld70.sm -1, xend=ld70.sm, y=0.85, yend=0.7), size = 0.1, color='grey30'
               arrow = arrow(length = unit(0.2, "cm"), type = "closed")) +
  annotate(geom="text", x=ld70.lm +1, y=0.0, label="LD70 by linear assumption",
           color="purple", hjust=0) +
  geom_segment(aes(x=1d70.lm +1, x=nd=1d70.lm, y=0.05, y=nd=0.7), size = 0.1, color='grey30'
               arrow = arrow(length = unit(0.2, "cm"), type = "closed"))
```

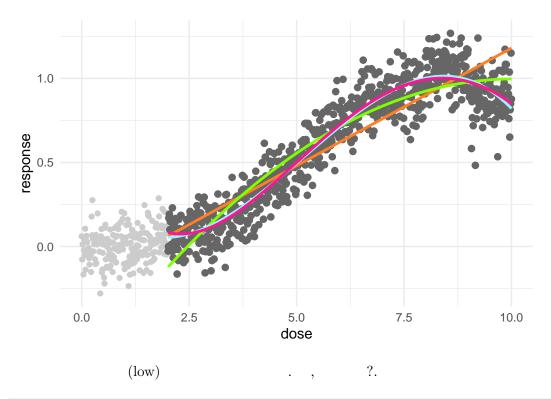


### 5.6

. Dose 2

```
# subcohort 2nd phase (1st phase is hospital base cohort)
s2c <- df %>% filter(dose >2)
s2m1<-lm(data=s2c, response ~ poly(dose, 1))
s2m2<-lm(data=s2c, response ~ poly(dose, 2))
s2m3<-lm(data=s2c, response ~ poly(dose, 3))
s2m4<-lm(data=s2c, response ~ poly(dose, 4))

df %>%
    ggplot(aes(x=dose, y=response)) +
    geom_point(color = 'grey80') + theme_minimal()+
    geom_point(data=s2c, color = 'grey40', size =2 ) +
    geom_line(data=s2c, aes(y=predict(s2m1)), color = 'chocolate1', size = 1) +
    geom_line(data=s2c, aes(y=predict(s2m2)), color = 'chartreuse1', size = 1) +
    geom_line(data=s2c, aes(y=predict(s2m3)), color = 'cadetblue1', size = 1) +
    geom_line(data=s2c, aes(y=predict(s2m4)), color = 'deeppink1', size = 1)
```



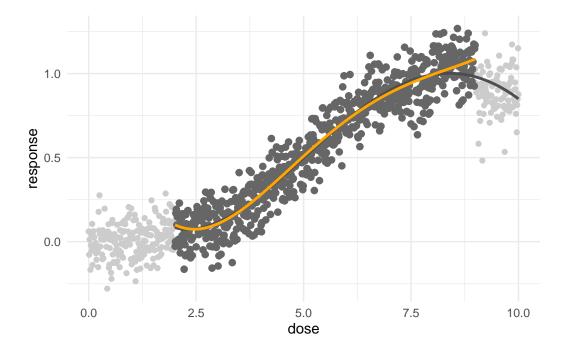
#### anova(s2m1, s2m2, s2m3, s2m4)

#### Analysis of Variance Table

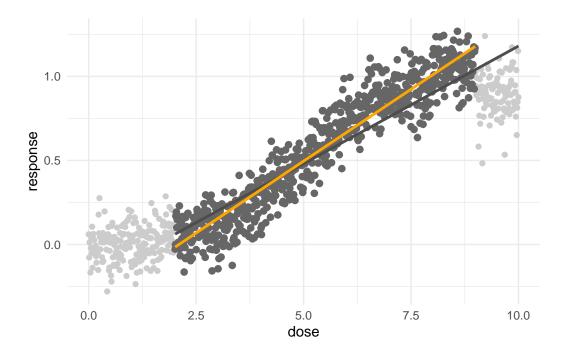
```
Model 1: response ~ poly(dose, 1)
Model 2: response ~ poly(dose, 2)
Model 3: response ~ poly(dose, 3)
Model 4: response ~ poly(dose, 4)
  Res.Df
             RSS Df Sum of Sq
                                     F Pr(>F)
1
     798 18.9099
2
     797 13.4734 1
                       5.4365 440.8574 < 2e-16 ***
                       3.5928 291.3455 < 2e-16 ***
3
     796 9.8806 1
     795 9.8036 1
                       0.0770
                                6.2423 0.01267 *
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
                     ? (
                                                         . )
  9
```

```
s3c <- df %>% filter(dose >2) %>% filter(dose <9)
s3m1<-lm(data=s3c, response ~ poly(dose, 1))
s3m2<-lm(data=s3c, response ~ poly(dose, 2))
s3m3<-lm(data=s3c, response ~ poly(dose, 3))
s3m4<-lm(data=s3c, response ~ poly(dose, 4))

df %>%
    ggplot(aes(x=dose, y=response)) +
    geom_point(color = 'grey80') + theme_minimal()+
    geom_point(data=s3c, color = 'grey40', size =2 ) +
    #geom_line(data=s2c, aes(y=predict(s2m1)), color = 'grey30', size = 1) +
    geom_line(data=s2c, aes(y=predict(s2m4)), color = 'grey30', size = 1) +
    #geom_line(data=s3c, aes(y=predict(s3m1)), color = 'orange', size = 1)
    geom_line(data=s3c, aes(y=predict(s3m4)), color = 'orange', size = 1)
```



```
df %>%
  ggplot(aes(x=dose, y=response)) +
  geom_point(color = 'grey80') + theme_minimal()+
  geom_point(data=s3c, color = 'grey40', size =2 ) +
  geom_line(data=s2c, aes(y=predict(s2m1)), color = 'grey30', size = 1) +
  #geom_line(data=s2c, aes(y=predict(s2m4)), color = 'grey30', size = 1) +
  geom_line(data=s3c, aes(y=predict(s3m1)), color = 'orange', size = 1)
```



#geom\_line(data=s3c, aes(y=predict(s3m4)), color = 'orange', size = 1)

```
library(gam)
######

s4c = df %>% filter(dose <9)
s4m1<-lm(data=s4c, response ~ poly(dose, 1))
s4m3<-lm(data=s4c, response ~ poly(dose, 3))
s4ms<-lm(data=s4c, response ~ sigmoid.f(dose-5))
s4mg<-gam(data=s4c, response ~ s(dose, 20))
anova(s4m1, s4m3, s4ms, s4mg)</pre>
```

#### Analysis of Variance Table

```
Model 1: response ~ poly(dose, 1)

Model 2: response ~ poly(dose, 3)

Model 3: response ~ sigmoid.f(dose - 5)

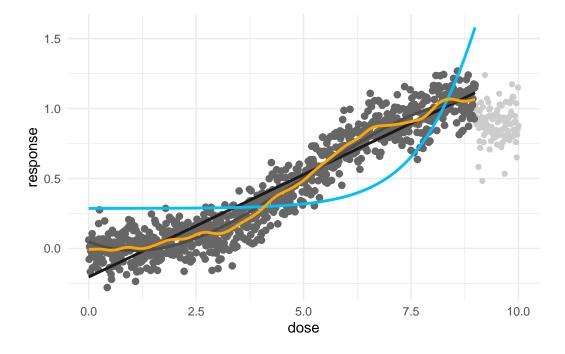
Model 4: response ~ s(dose, 20)

Res.Df RSS Df Sum of Sq F Pr(>F)

1 898 14.876
```

```
2 896 10.064 2.000 4.812 233.61 < 2.2e-16 ***
3 898 67.272 -2.000 -57.208 2777.26 < 2.2e-16 ***
4 879 9.053 18.999 58.219 297.52 < 2.2e-16 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
```

```
df %>%
  ggplot(aes(x=dose, y=response)) +
  geom_point(color = 'grey80') + theme_minimal()+
  geom_point(data=s4c, color = 'grey40', size =2 ) +
  geom_line(data=s4c, aes(y=predict(s4m1)), color = 'grey10', size = 1) +
  geom_line(data=s4c, aes(y=predict(s4m3)), color = 'grey30', size = 1) +
  geom_line(data=s4c, aes(y=predict(s4ms)), color = 'deepskyblue', size = 1) +
  geom_line(data=s4c, aes(y=predict(s4mg)), color = 'orange', size = 1)
```



#### 5.6.1 Take home message

1. :

• (SMR) . , -

2. :

```
• - , . , . . .
```

- 3. :
- - , .
- LD50( ) .
- ,
- 4. : , .

## 5.7 Threshold (change point )

threshold threshold point , piecewise regression , . . . . piecewise regression

threshold points (piecewise regression)	codes
total	$Resp = + 1 \cdot Dose + 2 \cdot (Dose - ) + + 0$
If Dose <	$Resp = + 1 \cdot Dose + 0$
If Dose >	$Resp = -2 \cdot + (1 + 2) \cdot Dose + 0$
model selection	minimal AIC value

#### 5.7.1

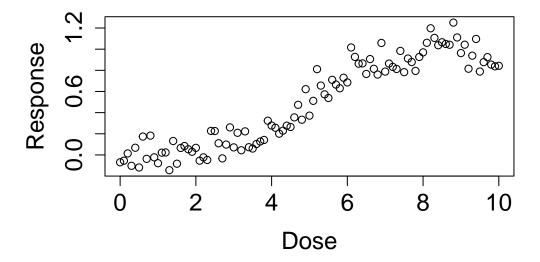
. (Dose) (Resp) . threshold .

```
set.seed(0)
dose <- seq(0,10, 0.1)
length(dose)</pre>
```

[1] 101

```
pb<-c(rnorm(50, 0, 0.001), rnorm(30, 0, 0.01), rnorm(10, 0.1, 0.05), rnorm(11, -0.1, 0.05))
resp <-1/(1+exp(-(dose-5)))+rnorm(length(dose), 0, 0.1)+pb

plot(dose, resp, xlab='Dose', ylab='Response', cex.lab=1.5, cex.axis=1.5, cex.main=1.5, cex.</pre>
```



```
cohort<-data.frame(dose, resp, pb)</pre>
```

#### 5.7.2 threshold

 $1\ 5$  . matrix (outdata) . outdata threshold point intercept, beta for before threshold, and its p value, beta for post threshold and its pvalue AIC . . therhold  $1\ 5$  .

```
cpdose <- ifelse(dose -1 >0, dose -1, 0)
cpm <- glm(resp ~ dose + cpdose)
summary(cpm)$aic</pre>
```

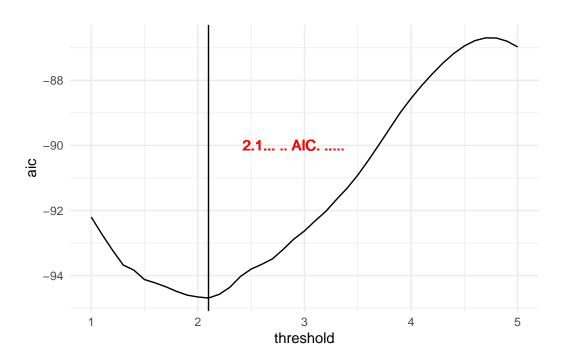
[1] -92.20184

```
cpdose <- ifelse(dose -5 >0, dose -5, 0)
cpm <- glm(resp ~ dose + cpdose)
summary(cpm)$aic</pre>
```

[1] -86.9744

? threshold 1  $\cdot$  2  $\cdot$  2.5  $\cdot$  .

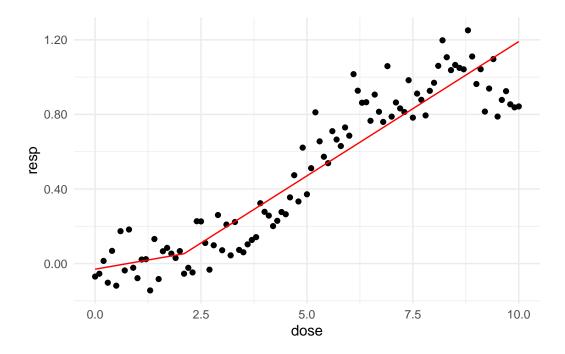
```
thr_fun <- function(thres){</pre>
cpdose <- ifelse(dose - thres >0, dose - thres, 0)
cpm <- glm(resp ~ dose + cpdose)</pre>
aic <- summary(cpm)$aic</pre>
data.frame(
 'threshold' = thres,
 'aic' = aic)
}
dose[which(dose == 1):which(dose == 5)]
 [1] 1.0 1.1 1.2 1.3 1.4 1.5 1.6 1.7 1.8 1.9 2.0 2.1 2.2 2.3 2.4 2.5 2.6 2.7 2.8
[20] 2.9 3.0 3.1 3.2 3.3 3.4 3.5 3.6 3.7 3.8 3.9 4.0 4.1 4.2 4.3 4.4 4.5 4.6 4.7
[39] 4.8 4.9 5.0
simul_list <- list()</pre>
simul_list <- lapply(dose[which(dose ==1):which(dose ==5)],</pre>
                                                                                    thr_fun
simul_dat <- do.call(rbind, simul_list)</pre>
library(ggplot2)
opt.thres <- simul_dat$threshold[which.min(simul_dat$aic)]</pre>
simul_dat %>%
  ggplot(aes(x = threshold, y = aic)) +
  geom_line() +
  geom_vline(xintercept = opt.thres) +
```



#### 2.1 threshold

```
thres = 2.1
f_cpdose <- ifelse(dose - thres >0, dose - thres, 0)
f_cpm <- glm(resp ~ dose + f_cpdose)</pre>
```

```
prepwlm <- predict(f_cpm)
scaleFUN <- function(x) sprintf("%.2f", x)
cohort %>%
    ggplot(aes(x= dose, y = resp)) +
    geom_point() +
    theme_minimal() +
    scale_y_continuous(labels = scaleFUN) +
    geom_line(aes(y = prepwlm), color ='red')
```

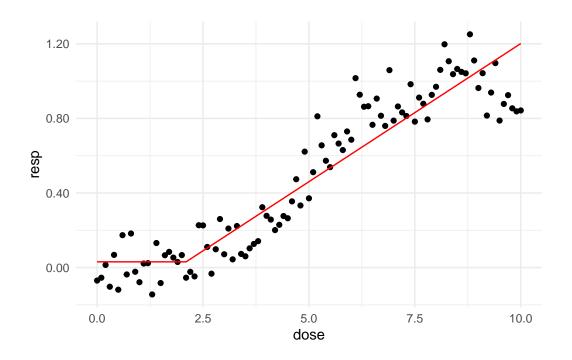


threshold

? dose predose

```
thres = 2.1
f_cpdose <- ifelse(dose - thres >=0, dose - thres, 0)
f_predose <- ifelse(dose - thres <=0, 0, dose - thres)
f_cpm <- glm(resp ~ f_predose + f_cpdose)</pre>
```

```
prepwlm <- predict(f_cpm)
scaleFUN <- function(x) sprintf("%.2f", x)
cohort %>%
    ggplot(aes(x= dose, y = resp)) +
    geom_point() +
    theme_minimal() +
    scale_y_continuous(labels = scaleFUN) +
    geom_line(aes(y = prepwlm), color = 'red')
```



## 6 - : Gompertz

(Gompertz)

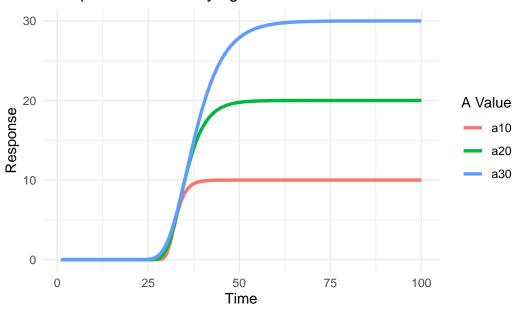
```
, investr
6.1 Gompertz
A:
         (asymptote) .
 (Mu):
                       (maximum slope) .
 (Lambda):
                     (lag-phase) . ,
if(!require("tidyverse")) install.packages("tidyverse");library(tidyverse)
if(!require("nls.multstart")) install.packages("nls.multstart"); library(nls.multstart)
if(!require("investr")) install.packages("investr"); library(investr)
# Gompertz
gompertz <- function(time, a, mu, lambda) {</pre>
  a * exp(-exp(mu * exp(1) / a * (lambda - time) + 1))
}
     Gompertz
# A
tibble(time = 1:100) %>%
  mutate(
    a10 = gompertz(time, a = 10, mu = 2, lambda = 30),
    a20 = gompertz(time, a = 20, mu = 2, lambda = 30),
    a30 = gompertz(time, a = 30, mu = 2, lambda = 30)
  ) %>%
  pivot longer(
    cols = starts_with("a"),
```

. ggplot2 , nls.multstart

```
names_to = "parameter_a",
    values_to = "response"
) %>%

ggplot(aes(x = time, y = response, color = parameter_a)) +
geom_line(size = 1.2) +
labs(
    title = "Gompertz Curve: Varying 'A'",
    x = "Time",
    y = "Response",
    color = "A Value"
) +
theme_minimal()
```

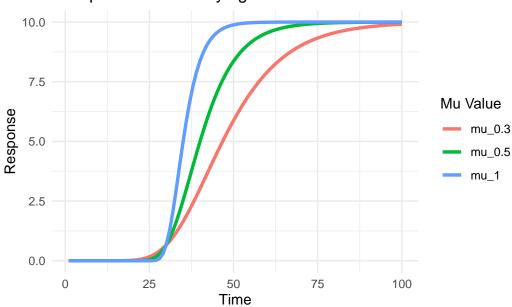
## Gompertz Curve: Varying 'A'



```
# Gompertz
# Mu
tibble(time = 1:100) %>%
    mutate(
        mu_1 = gompertz(time, a = 10, mu = 1, lambda = 30),
        mu_0.5 = gompertz(time, a = 10, mu = 0.5, lambda = 30),
        mu_0.3 = gompertz(time, a = 10, mu = 0.3, lambda = 30)
) %>%
    pivot_longer(
```

```
cols = starts_with("m"),
  names_to = "parameter_a",
  values_to = "response"
) %>%
ggplot(aes(x = time, y = response, color = parameter_a)) +
geom_line(size = 1.2) +
labs(
  title = "Gompertz Curve: Varying 'Mu'",
  x = "Time",
  y = "Response",
  color = "Mu Value"
) +
theme_minimal()
```

## Gompertz Curve: Varying 'Mu'

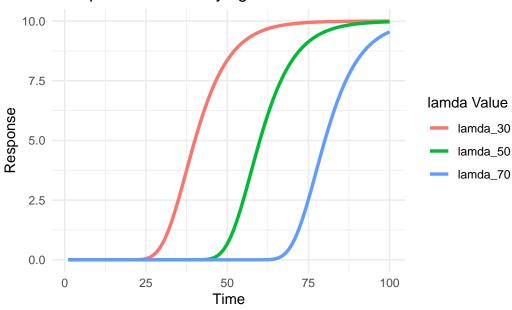


```
# Gompertz
# lamda
tibble(time = 1:100) %>%
    mutate(
    lamda_30 = gompertz(time, a = 10, mu = 0.5, lambda = 30),
    lamda_50 = gompertz(time, a = 10, mu = 0.5, lambda = 50),
    lamda_70 = gompertz(time, a = 10, mu = 0.5, lambda = 70)
) %>%
```

```
pivot_longer(
   cols = starts_with("l"),
   names_to = "parameter_a",
   values_to = "response"
) %>%

ggplot(aes(x = time, y = response, color = parameter_a)) +
geom_line(size = 1.2) +
labs(
   title = "Gompertz Curve: Varying 'lamda'",
   x = "Time",
   y = "Response",
   color = "lamda Value"
) +
theme_minimal()
```

## Gompertz Curve: Varying 'lamda'



#### 6.1.0.1

- tibble ggplot2 , , .

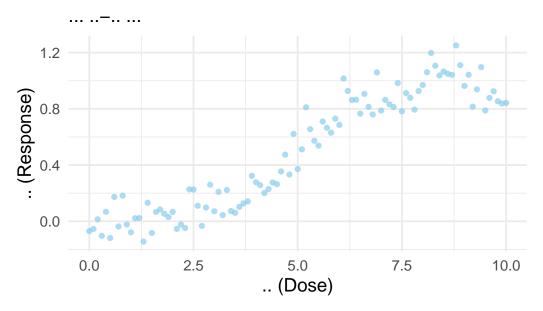
```
#
set.seed(0)
```

```
dose <- seq(0, 10, 0.1)
pb <- c(rnorm(50, 0, 0.001), rnorm(30, 0, 0.01), rnorm(10, 0.1, 0.05), rnorm(11, -0.1, 0.05)
resp <- 1 / (1 + exp(-(dose - 5))) + rnorm(length(dose), 0, 0.1) + pb

# tibble
cohort <- tibble(dose, resp, pb)

ggplot(cohort, aes(x = dose, y = resp)) +
    geom_point(color = "skyblue", alpha = 0.7) +
    labs(
        title = "Dose-Response Relationship",
        subtitle = " - ",
        x = " (Dose)",
        y = " (Response)"
    ) +
    theme_minimal(base_size = 14) +
    theme(plot.title = element_text(face = "bold"))</pre>
```

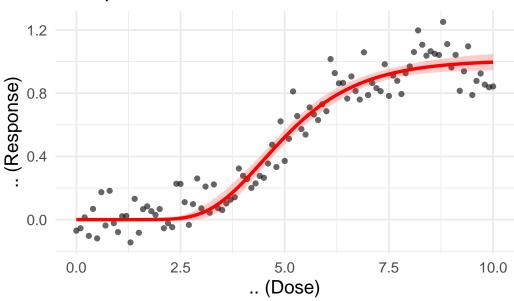
## **Dose-Response Relationship**



#### 6.1.0.2 Gompertz

```
# nls_multstart
nls_fit <- nls_multstart(</pre>
 resp ~ gompertz(dose, a, mu, lambda),
 data = cohort,
 start_lower = c(a = 0, mu = 0, lambda = 0),
 start\_upper = c(a = 2, mu = 1, lambda = 10),
 iter = 250
)
Error in nlsModel(formula, mf, start, wts) :
  singular gradient matrix at initial parameter estimates
Error in nlsModel(formula, mf, start, wts) :
  singular gradient matrix at initial parameter estimates
Error in nlsModel(formula, mf, start, wts) :
  singular gradient matrix at initial parameter estimates
Error in nlsModel(formula, mf, start, wts) :
  singular gradient matrix at initial parameter estimates
print(summary(nls_fit))
Formula: resp ~ gompertz(dose, a, mu, lambda)
Parameters:
      Estimate Std. Error t value Pr(>|t|)
       mu
lambda 3.20596 0.15811 20.28 <2e-16 ***
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.1106 on 98 degrees of freedom
Number of iterations to convergence: 23
Achieved convergence tolerance: 1.49e-08
#
cohort_ci <- investr::predFit(</pre>
nls_fit,
```

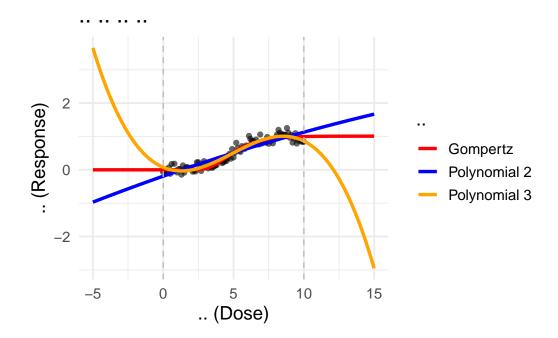
## Gompertz .... 95% ....



#### **6.1.0.3 3:** (Extrapolation)

```
. AIC(Akaike Information Criterion) , AIC . AIC , (Extrapolation) . (dose -5 \sim 0 10 \sim 15) , Gompertz .
```

```
poly2_fit <- glm(resp ~ poly(dose,2),data = cohort)</pre>
poly3_fit <- glm(resp ~ poly(dose,3),data = cohort)</pre>
# AIC
AIC(nls_fit, poly2_fit, poly3_fit)
                    AIC
          df
nls_fit
           4 -153.22741
poly2_fit 4 -87.32223
poly3_fit 5 -154.38409
     (extrapolation)
extrapolated_data <- tibble(dose = seq(-5, 15, length.out = 100))
extrapolated_data <- extrapolated_data %>%
  mutate(
    gompertz_pred = predict(nls_fit, newdata = .),
    poly2_pred = predict(poly2_fit, newdata = .),
    poly3_pred = predict(poly3_fit, newdata = .)
ggplot(cohort, aes(x = dose, y = resp)) +
  geom_point(alpha = 0.6) +
  geom_line(data = extrapolated_data, aes(y = gompertz_pred, color = "Gompertz"), size = 1.2
  geom_line(data = extrapolated_data, aes(y = poly2_pred, color = "Polynomial 2"), size = 1.
  geom_line(data = extrapolated_data, aes(y = poly3_pred, color = "Polynomial 3"), size = 1.3
  geom_vline(xintercept = range(cohort$dose), linetype = "dashed", color = "gray") +
  scale_color_manual(values = c("Gompertz" = "red", "Polynomial 2" = "blue", "Polynomial 3";
                       ", x = " (Dose)", y = " (Response)", color = " ") +
  labs(title = "
  theme_minimal(base_size = 14)
```



## 7 MixedModel

```
if(!require("tidyverse")) install.packages("tidyverse");library(tidyverse)
if(!require("nls.multstart")) install.packages("nls.multstart"); library(nls.multstart)
if(!require("investr")) install.packages("investr");library(investr)
if(!require("nlme")) install.packages("nlme");library(nlme)
if(!require("boot")) install.packages("boot");library(boot)
            (Gompertz)
7.1
            (Gompertz, Logistic)
                                         (Hill)
7.1.1
       : y(dose) = fraca1 + exp(-b(dose-c))
       - S
       – a:
       - b: ( )
       - c: LD50( 50%
      : y(dose)=fracacdotdosebcb+doseb
       – b:
             (Hill Coefficient), ( )
       - c: LD50(50\%)
```

#### 7.1.2 :

```
(Gompertz, Logistic, Hill) , AIC(Akaike Information Criterion) . AIC , AIC .
```

```
# Gompertz
gompertz <- function(dose, a, mu, lambda) {</pre>
  a * exp(-exp(mu * exp(1) / a * (lambda - dose) + 1))
logistic <- function(dose, a, b, c) {</pre>
a / (1 + exp(-b * (dose - c)))
hill <- function(dose, a, b, c) {
 (a * dose^b) / (c^b + dose^b)
# LD50
ld50_logistic <- function(model) {</pre>
  coefs <- coef(model)</pre>
  ld50 <- coefs["c"]</pre>
  return(1d50)
set.seed(0)
dose <- seq(0, 10, 0.1)
pb <- c(rnorm(50, 0, 0.001), rnorm(30, 0, 0.01), rnorm(10, 0.1, 0.05), rnorm(11, -0.1, 0.05)
resp <-1 / (1 + \exp(-(dose - 5))) + rnorm(length(dose), 0, 0.1) + pb
cohort <- tibble(dose, resp)</pre>
nls_gompertz <- nls_multstart(</pre>
 resp ~ gompertz(dose, a, mu, lambda),
  data = cohort,
  start_lower = c(a = 0, mu = 0, lambda = 0),
  start\_upper = c(a = 2, mu = 1, lambda = 10),
  iter = 250 # iter
)
```

```
Error in nlsModel(formula, mf, start, wts) :
  singular gradient matrix at initial parameter estimates
Error in nlsModel(formula, mf, start, wts) :
  singular gradient matrix at initial parameter estimates
Error in nlsModel(formula, mf, start, wts) :
  singular gradient matrix at initial parameter estimates
Error in nlsModel(formula, mf, start, wts) :
  singular gradient matrix at initial parameter estimates
nls_logistic <- nls_multstart(</pre>
  resp ~ logistic(dose, a, b, c),
  data = cohort,
  start_lower = c(a = 0, b = 0, c = 0),
  start_upper = c(a = 2, b = 1, c = 10),
  iter = 250 # iter
Error in nlsModel(formula, mf, start, wts) :
  singular gradient matrix at initial parameter estimates
Error in nlsModel(formula, mf, start, wts) :
  singular gradient matrix at initial parameter estimates
Error in nlsModel(formula, mf, start, wts) :
  singular gradient matrix at initial parameter estimates
Error in nlsModel(formula, mf, start, wts) :
  singular gradient matrix at initial parameter estimates
Error in nlsModel(formula, mf, start, wts) :
  singular gradient matrix at initial parameter estimates
Error in nlsModel(formula, mf, start, wts) :
  singular gradient matrix at initial parameter estimates
Error in nlsModel(formula, mf, start, wts) :
  singular gradient matrix at initial parameter estimates
Error in nlsModel(formula, mf, start, wts) :
  singular gradient matrix at initial parameter estimates
Error in nlsModel(formula, mf, start, wts) :
  singular gradient matrix at initial parameter estimates
Error in nlsModel(formula, mf, start, wts) :
  singular gradient matrix at initial parameter estimates
nls_hill <- nls_multstart(</pre>
  resp ~ hill(dose, a, b, c),
```

```
data = cohort,
start_lower = c(a = 0, b = 0, c = 0),
```

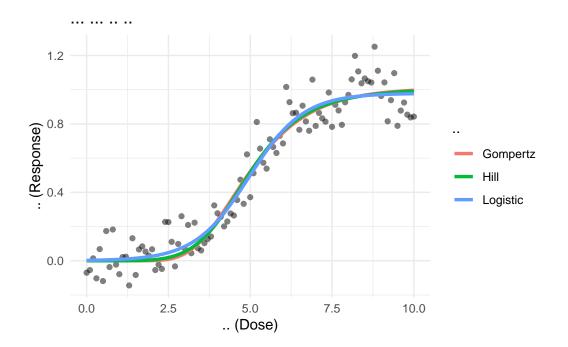
```
start_upper = c(a = 2, b = 10, c = 10),
 iter = 250 # iter
# AIC
aic_values <- AIC(nls_gompertz, nls_logistic, nls_hill)</pre>
print(aic_values)
            df AIC
nls_gompertz 4 -153.2274
nls_logistic 4 -160.6434
nls_hill 4 -156.0963
    AIC
                                         AIC
                           nls\_gompertz -153.2274
                           nls logistic
                                         -160.6434
                           nls hill
                                        -156.0963
```

Logistic AIC -160.6434 .

,

```
#
cohort_predicted <- cohort %>%
  mutate(
    Gompertz = predict(nls_gompertz),
    Logistic = predict(nls_logistic),
    Hill = predict(nls_hill)
) %>%
  pivot_longer(
    cols = c(Gompertz, Logistic, Hill),
    names_to = "Model",
    values_to = "Predicted_Response"
)

ggplot(cohort, aes(x = dose, y = resp)) +
    geom_point(alpha = 0.5) +
```



## 7.2 : (Covariates)

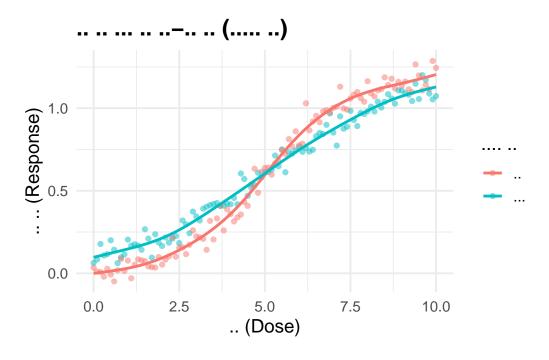
7.2.1 :

.

• :

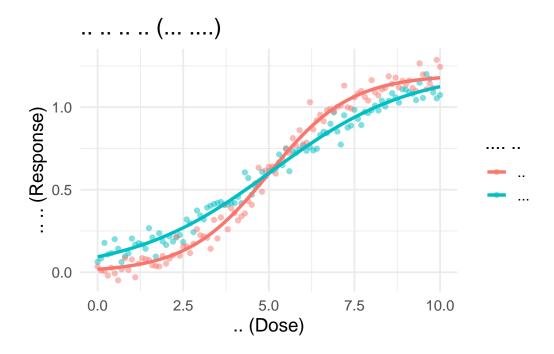
• : . , . . .

```
# nlme
library(nlme)
library(tidyverse)
# Gompertz
gompertz <- function(dose, a, mu, lambda) {</pre>
 a / (1 + exp(-mu * (dose - lambda)))
set.seed(123)
dose <- seq(0, 10, 0.1)
n_dose <- length(dose)</pre>
             ( Gompertz )
resp_nonshift <- gompertz(dose, a = 1.2, mu = 0.5, lambda = 5) + rnorm(n_dose, 0, 0.05)
                Gompertz )
resp_shift <- gompertz(dose, a = 1.2, mu = 0.8, lambda = 5) + rnorm(n_dose, 0, 0.05)
cohort_full <- tibble(</pre>
 dose = rep(dose, 2),
 shift = factor(c(rep(" ", n_dose), rep(" ", n_dose))),
 resp = c(resp_nonshift, resp_shift)
)
ggplot(cohort_full, aes(x = dose, y = resp, color = shift)) +
  geom_point(alpha = 0.5) +
 geom_smooth(method = "gam", formula = y ~ s(x), se = FALSE) +
  labs(
                      - ( )",
   title = "
   x = " (Dose)",
   y = " (Response)",
   color = " "
  ) +
  theme_minimal(base_size = 14) +
  theme(plot.title = element_text(face = "bold"))
```



```
Gompertz
# fixed = a + mu + lam ~ shift shift
                                               a, mu, lam
nlme_fit <- nlme(</pre>
  model = resp \sim a / (1 + exp(-(mu * (dose - lam)))),
  data = cohort_full,
  fixed = a + mu + lam ~ shift,
  random = a + mu + lam ~ 1 | shift,
  start = c(a = c(1.2, 1.2), mu = c(0.5, 0.8), lam = c(5, 5)),
  control = list(pnlsTol = 0.01)
#summary(nlme_fit)
cohort_full$nlme_pred <- predict(nlme_fit)</pre>
ggplot(cohort_full, aes(x = dose, y = resp, color = shift)) +
  geom_point(alpha = 0.5) +
  geom_line(aes(y = nlme_pred, group = shift), size = 1.2) +
  labs(
   title = "
```

```
x = " (Dose)",
y = " (Response)",
color = " "
) +
theme_minimal(base_size = 14)
```



#### summary(nlme\_fit)

```
Nonlinear mixed-effects model fit by maximum likelihood
  Model: resp \sim a/(1 + exp(-(mu * (dose - lam))))
  Data: cohort_full
        AIC
                  BIC
                        logLik
  -634.3112 -591.3037 330.1556
Random effects:
 Formula: list(a ~ 1, mu ~ 1, lam ~ 1)
 Level: shift
 Structure: General positive-definite, Log-Cholesky parametrization
                StdDev
                             Corr
a.(Intercept)
                9.047340e-07 a.(In) m.(In)
mu.(Intercept) 1.149202e-06 0
lam.(Intercept) 1.844210e-06 0
```

#### Residual 4.719949e-02

a.shift

```
Fixed effects: a + mu + lam ~ shift
                   Value Std.Error DF t-value p-value
                1.195727 0.01404366 195 85.14359 0.0000
a.(Intercept)
a.shift
            0.029480 0.03142533 195 0.93811 0.3493
mu.(Intercept)
                0.835771 0.02898145 195 28.83812 0.0000
           -0.345475 0.03510659 195 -9.84075 0.0000
lam.(Intercept) 5.000389 0.05323858 195 93.92415 0.0000
            0.082515 0.14068227 195 0.58653 0.5582
lam.shift
 Correlation:
               a.(In) ashft m.(In) mshft lm.(I)
           -0.447
a.shift
mu.(Intercept) -0.685 0.306
           0.565 -0.680 -0.826
lam.(Intercept) 0.770 -0.344 -0.527 0.435
lam.shift -0.291 0.910 0.200 -0.581 -0.378
Standardized Within-Group Residuals:
        Min
                    Q1
                               Med
                                            Q3
                                                       Max
-2.53316379 -0.67449163 -0.07048116 0.62151401 3.28479392
Number of Observations: 202
Number of Groups: 2
# p-value (tidy )
# fixed effects .
#fixed_effects <- summary(nlme_fit)$tTable</pre>
# p-value . (t-value (DF) )
#p_values <- 2 * (1 - pt(abs(fixed_effects[, "t-value"]), fixed_effects[, "DF"]))</pre>
    p-value summary
#fixed_effects_with_p <- cbind(fixed_effects, `p-value` = p_values)</pre>
#print(fixed_effects_with_p)
                               . summary(nlme fit)
                           (Value)
                                        p-value
           a.(Intercept) 1.195727
                                        0.0000
                                                             (a)**
```

0.3493

0.0000

p-value 0.05

(mu)\*\* .

0.029480

mu.(Intercept) 0.835771

	mu.shift	-0.345475	0.0000	. p-	mu value 0.0001	,
	<pre>lam.(Intercept) lam.shift</pre>	5.000389 0.082515	$0.0000 \\ 0.5582$	**	(lam)** . lam	
**'	(mu)		·**			