

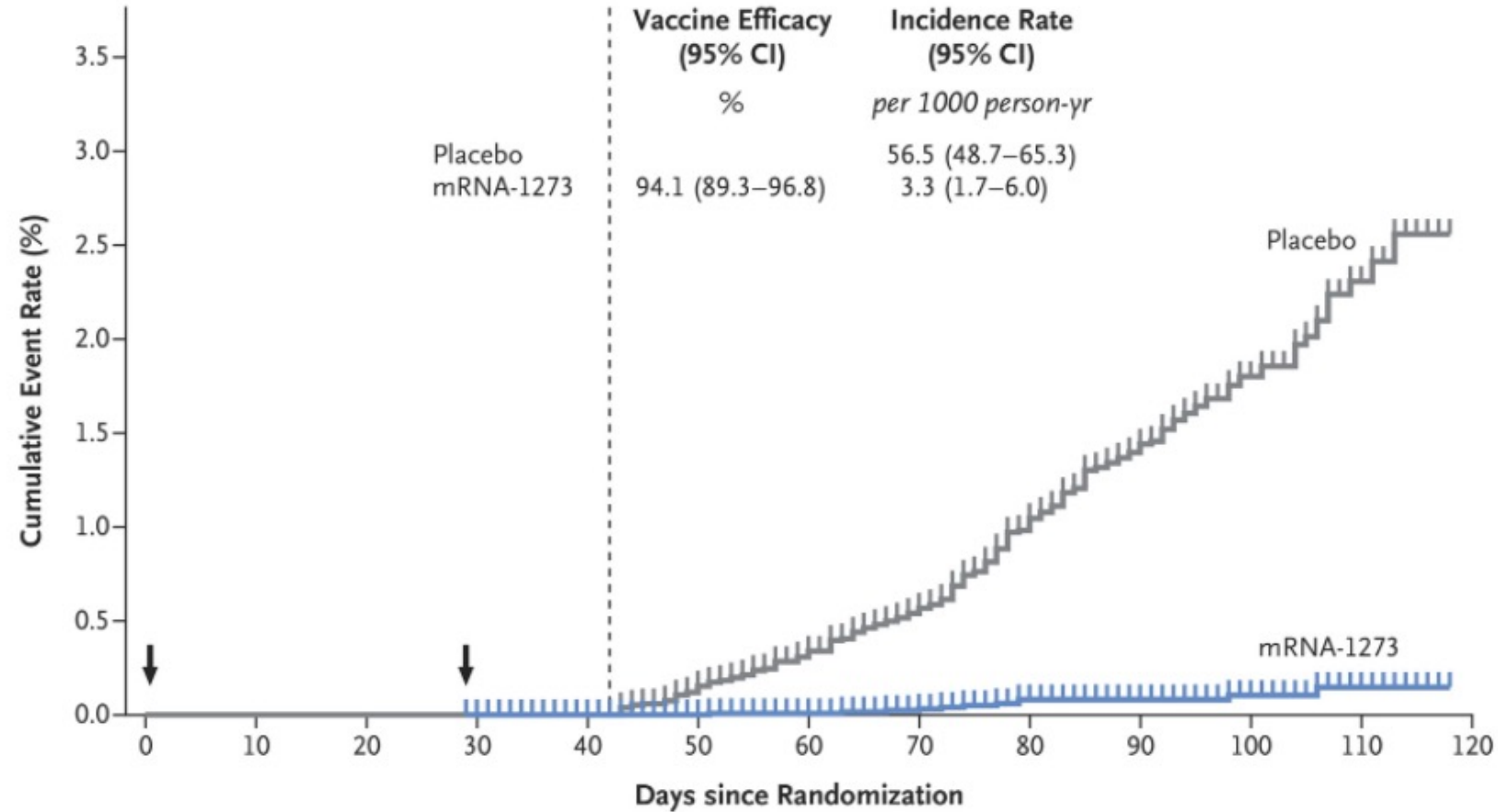
Survival Analysis

February 16, 2022

Why survival analysis?

- "time to event" data
- commonly used in clinical trial settings - time to outcome (usually something bad)

A Per-Protocol Analysis



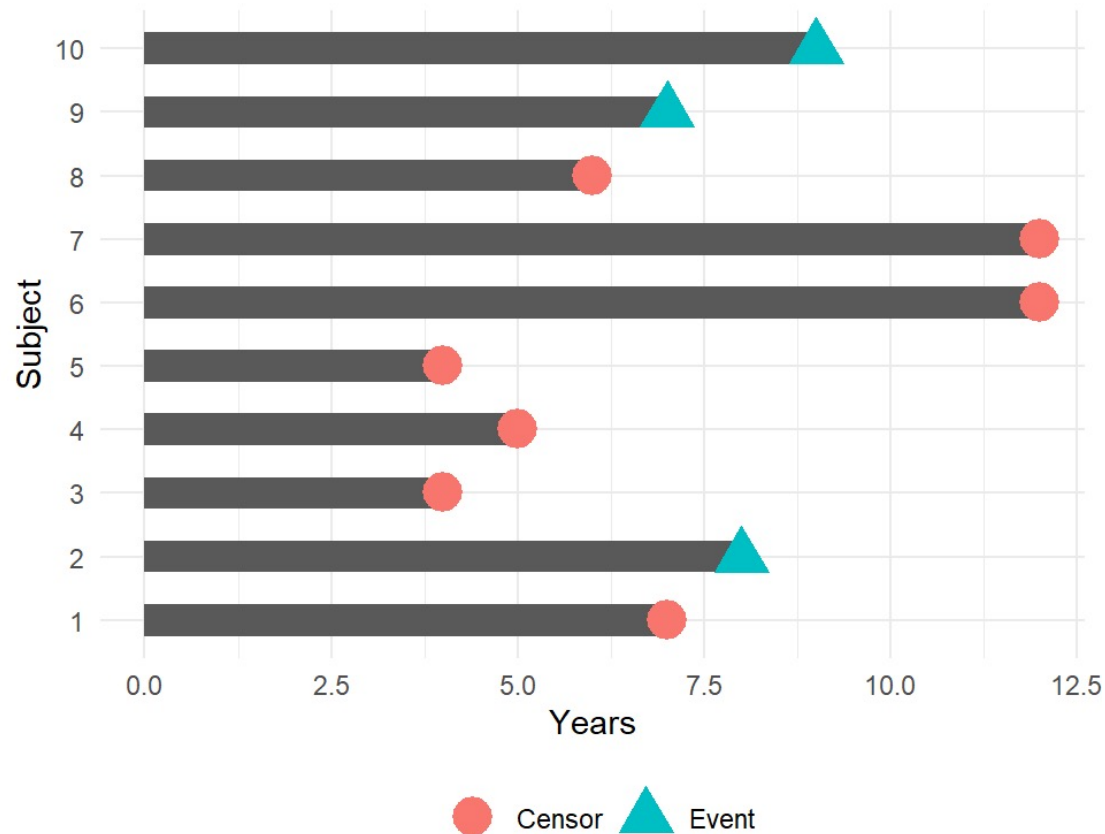
No. at Risk

Placebo	14,073	14,073	14,073	14,072	13,416	12,992	12,361	11,147	9474	6563	3971	1172	0
mRNA-1273	14,134	14,134	14,134	14,133	13,483	13,073	12,508	11,315	9684	6721	4094	1209	0

Why survival analysis?

- Why do we need a special method for time to event data?
- **censoring** - we may end observation before we determine whether an event has occurred or not. Ignoring censoring generates inaccurate estimates of probability of an outcome
- typically data are **right-censored** - outcome not observed by end of observation period. (Data can also be left-censored or interval-censored)

Censored survival data



How to compute proportion of subjects that are event-free at 10 years?

6, 7 were event-free at 10 years

2, 9, and 10 had the event before 10 years

1, 3, 4, 5, 8 were censored before 10 years.
Data collection ended, but we don't know whether or not they had the event –
how to incorporate into the estimate?

Survival data

- "time to event" data have 2 components:
 - observed time (minimum of event time and censoring time)
 - event indicator: convention is 1 if event observed, 0 if censored
- R uses `Surv` function (CAPITAL S) from the `survival` package to compose a "survival object"
 - 1 if event observed, 0 if censored
 - will also accept TRUE/FALSE (TRUE = event) or 1/2 (2 = event)
 - `Surv(time, event)`

Survival data

- `Surv` object combines times and censoring information for use in specialized functions to deal with time-to-event data

```
> Surv(fkdt$Years, fkdt$censor_01)
[1] 7+ 8 4+ 5+ 4+ 12+ 12+ 6+ 7 9
```

Kaplan-Meier curve

- Nonparametric function (does not depend on any theoretical distribution function)
- Product of proportions known to survive at times up to and including time of event i

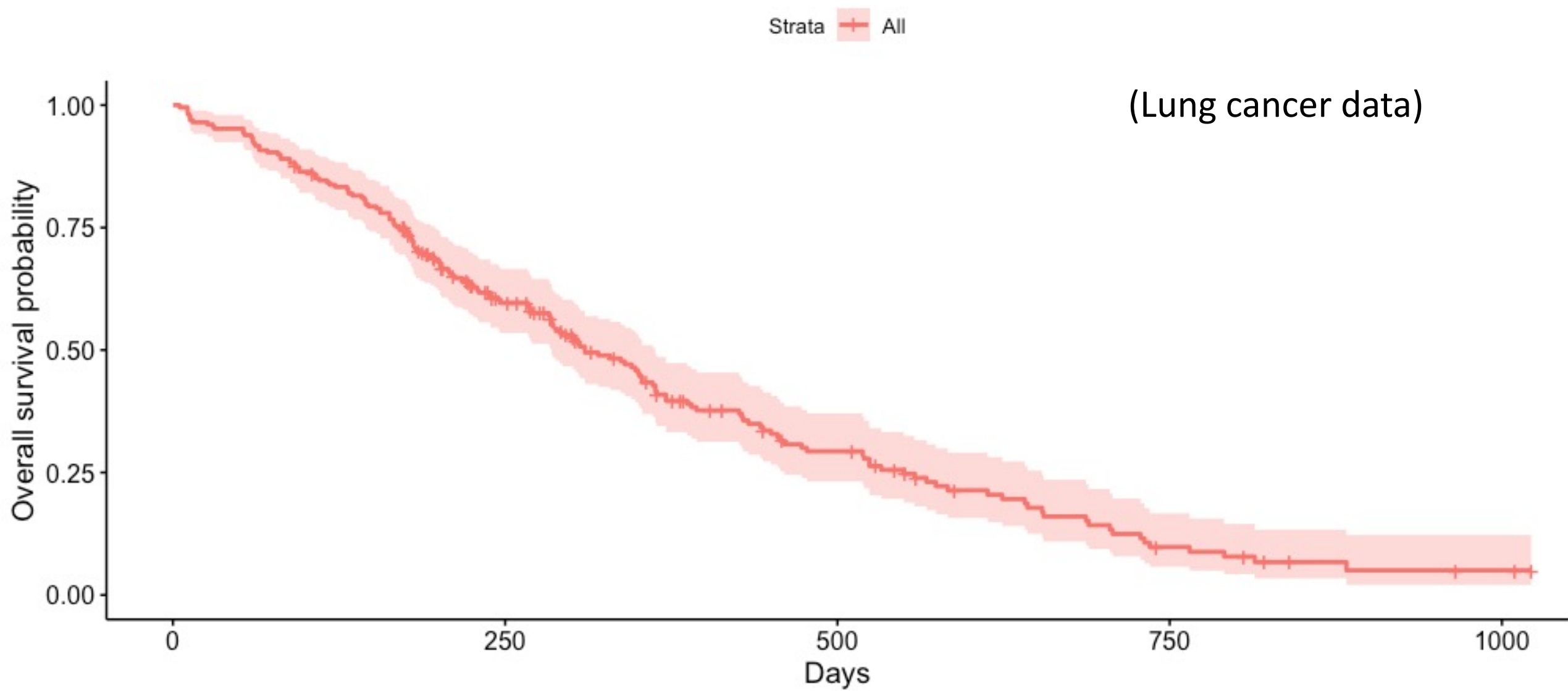
$$\text{estimate of survival at time } t = \prod_{i: t_i \leq t} \left(1 - \frac{\text{number of events at time } i}{\text{number known not to have had an event at time } i} \right)$$

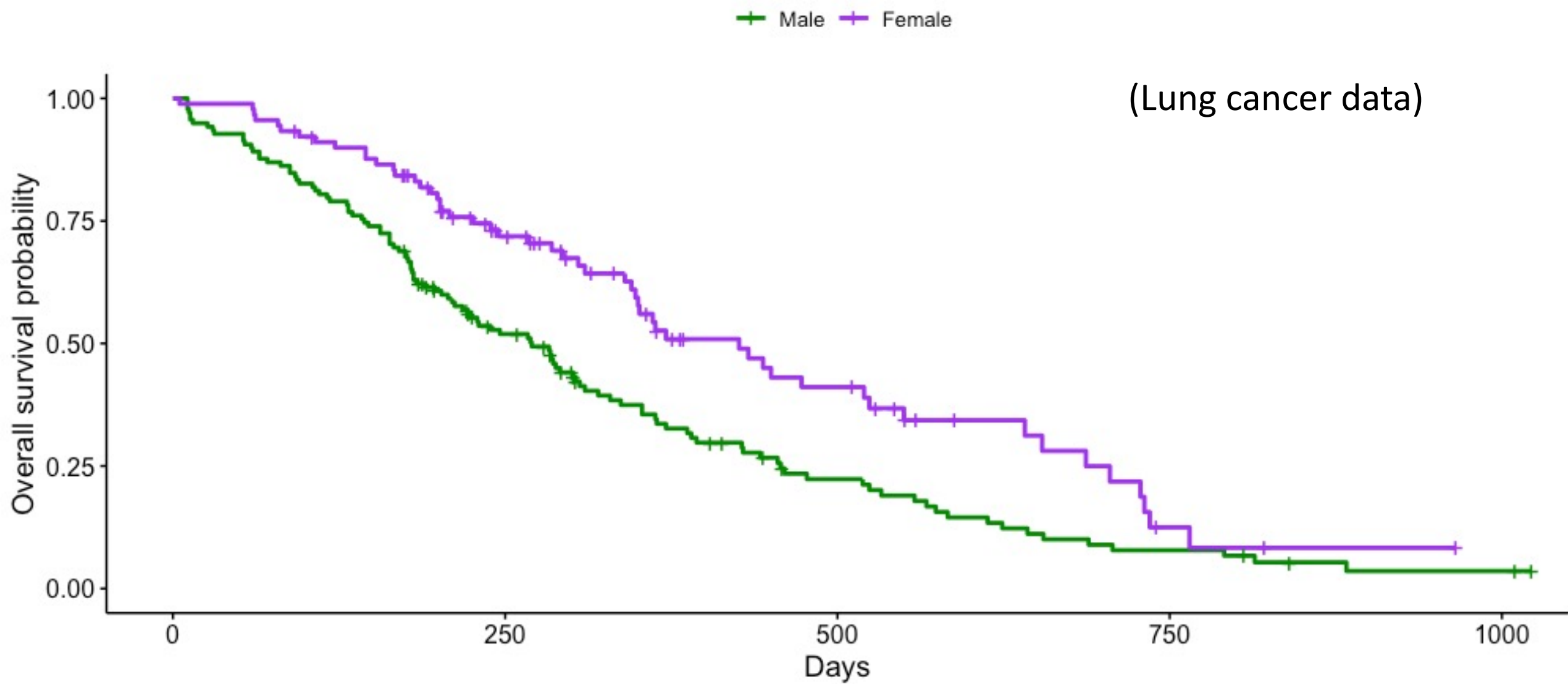
Kaplan-Meier curve

$$\text{estimate of survival at time } t = \prod_{i: t_i \leq t} \left(1 - \frac{\text{number of events at time } i}{\text{number known not to have had an event by time } i} \right)$$

- First event is at time point 7 in our sample data
- K-M estimate at time 7 is $1 \times \left(1 - \frac{1}{6} \right) = 0.833$
 - 4 cases censored before time 7
- K-M estimate at time 8 is $1 \times \left(1 - \frac{1}{6} \right) \left(1 - \frac{1}{4} \right) = 0.625$
 - 2 more cases before time 8 (at time 7): 1 censored, one had an event
- K-M estimate at time 9 is $1 \times \left(1 - \frac{1}{6} \right) \left(1 - \frac{1}{4} \right) \left(1 - \frac{1}{3} \right) = 0.4167$
 - 1 more case lost before time 9 (at time 8): 1 event
- Estimate does not change after this point because there are no more events, only censored cases

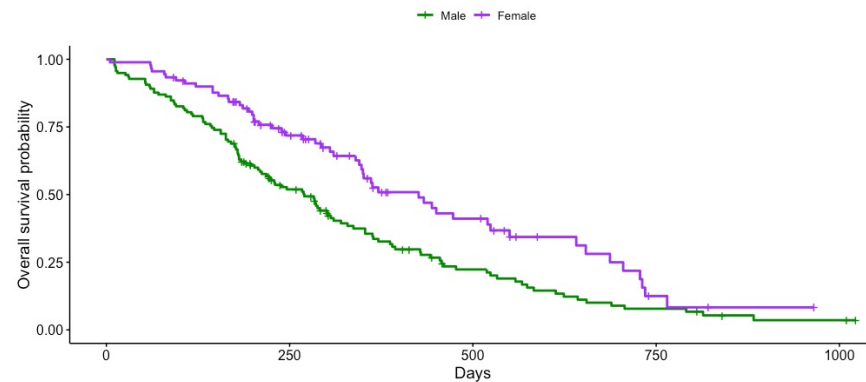
```
> Surv(fkdt$Years, fkdt$censor_01)
[1] 7+ 8 4+ 5+ 4+ 12+ 12+ 6+ 7 9
```





Comparison of survival curves

- "Log-rank" test works for comparing on single factor



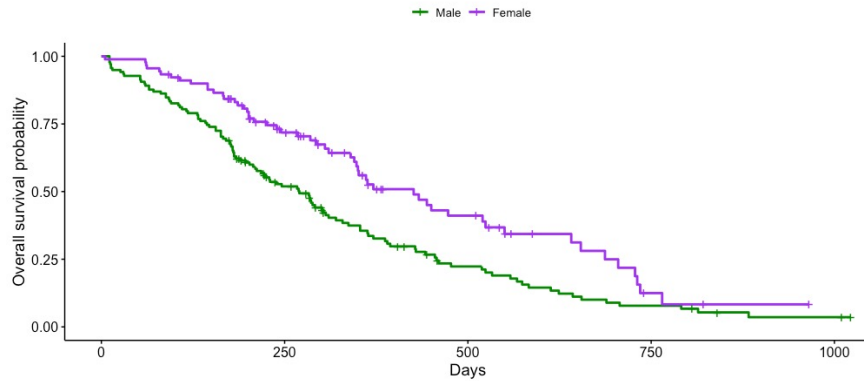
```
> survdiff(Surv(time, status) ~ sex, data = lung)
Call:
survdiff(formula = Surv(time, status) ~ sex, data = lung)

          N Observed Expected (O-E)^2/E (O-E)^2/V
sex=1 138      112      91.6      4.55      10.3
sex=2  90       53      73.4      5.68      10.3

Chisq= 10.3 on 1 degrees of freedom, p= 0.001
```

- Cox proportional hazards regression allows more complex designs
 - Assumes ratio of hazards for any 2 individuals at any time point is constant
 - Does not allow K-M curves that cross or have different shapes (one stops but other does not)

Cox proportional hazards regression



```
> coxph(Surv(time, status) ~ sex, data = lung) %>% summary()
Call:
coxph(formula = Surv(time, status) ~ sex, data = lung)

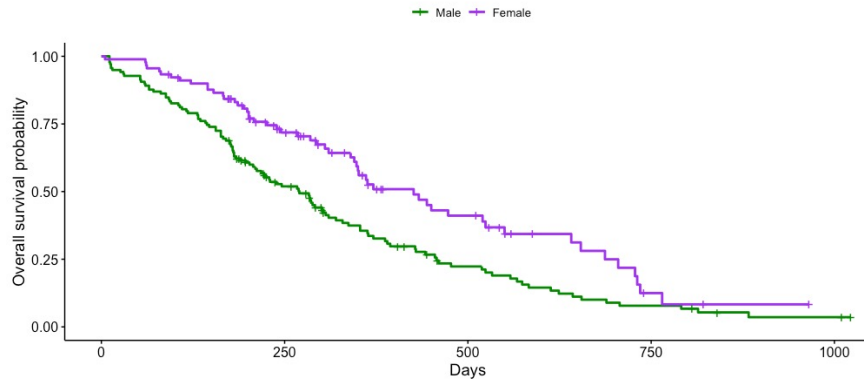
n= 228, number of events= 165

              coef exp(coef) se(coef)      z Pr(>|z|)
sex -0.5310      0.5880   0.1672 -3.176  0.00149 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

              exp(coef) exp(-coef) lower .95 upper .95
sex              0.588      1.701   0.4237   0.816

Concordance= 0.579 (se = 0.021 )
Likelihood ratio test= 10.63  on 1 df,   p=0.001
Wald test               = 10.09  on 1 df,   p=0.001
Score (logrank) test = 10.33  on 1 df,   p=0.001
```

Cox proportional hazards regression



exponentiated estimated coefficient is hazard ratio

at any one time, expect 0.588 females have died for every 1 male that has died

```
> coxph(Surv(time, status) ~ sex, data = lung) %>% summary()
Call:
coxph(formula = Surv(time, status) ~ sex, data = lung)

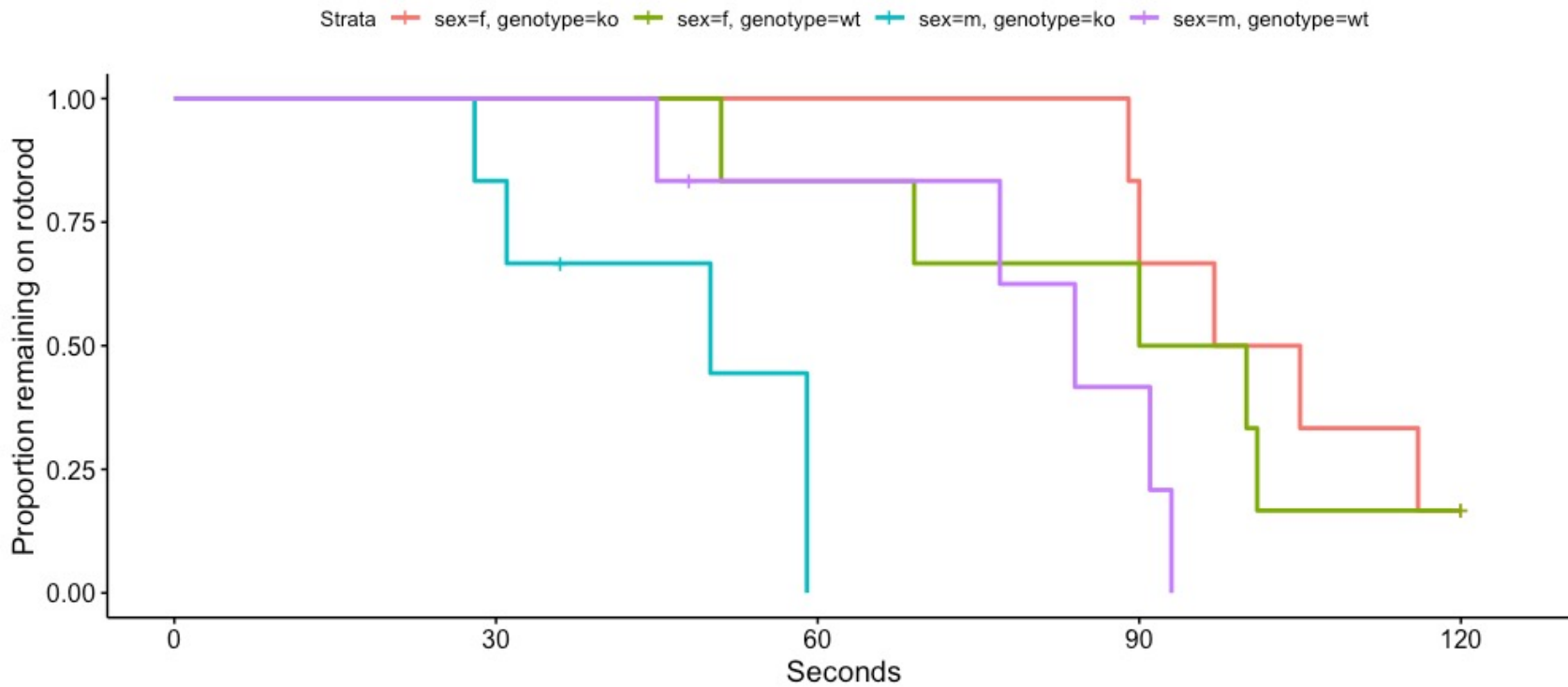
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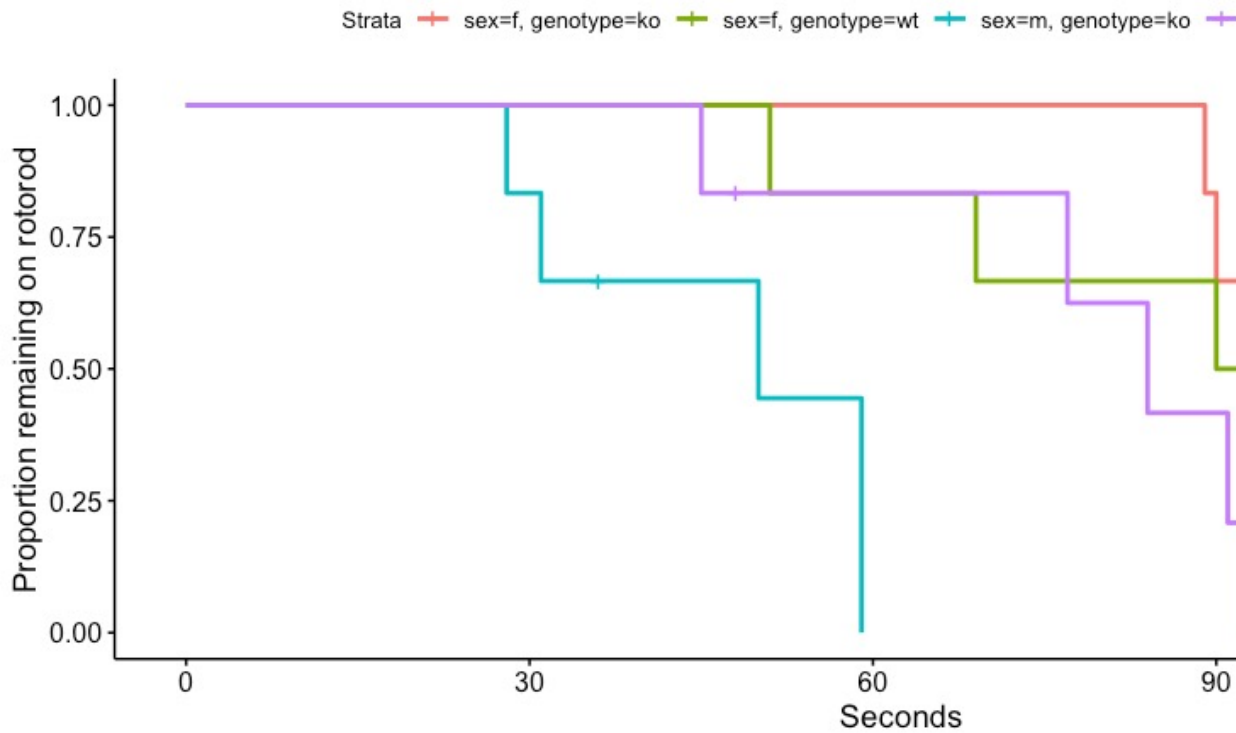
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```

Cox proportional hazards regression



Cox proportional hazards regression



```
Call:
coxph(formula = Surv(time, outcome_cens) ~ sex * genotype, data = rotorod)
```

```
n= 24, number of events= 20
```

	coef	exp(coef)	se(coef)	z	Pr(> z)
sexm	3.51034	33.45972	0.99699	3.521	0.00043 ***
genotypewt	0.37909	1.46095	0.63901	0.593	0.55302
sexm:genotypewt	-2.43819	0.08732	1.10864	-2.199	0.02786 *

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

	exp(coef)	exp(-coef)	lower .95	upper .95
sexm	33.45972	0.02989	4.741154	236.135
genotypewt	1.46095	0.68449	0.417553	5.112
sexm:genotypewt	0.08732	11.45235	0.009941	0.767

```
Concordance= 0.755 (se = 0.04 )
```

```
Likelihood ratio test= 15.72 on 3 df, p=0.001
```

```
Wald test = 13.22 on 3 df, p=0.004
```

```
Score (logrank) test = 21.09 on 3 df, p=1e-04
```