

# Penalized Power-Generalized Weibull Distributional Regression

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## Background

- Covariates usually enter a parametric hazard function,  $\lambda(t)$ , through the scale parameter only. This is the case for the popular proportional hazards (PH) model.
- $\lambda(t)$  is used to express the risk of a particular event occurring at time t.
- By adopting a multi-parameter regression (MPR) technique, where multiple distributional parameters depend on covariates, further flexibility can be achieved.

## Power-Generalized Weibull (PGW)

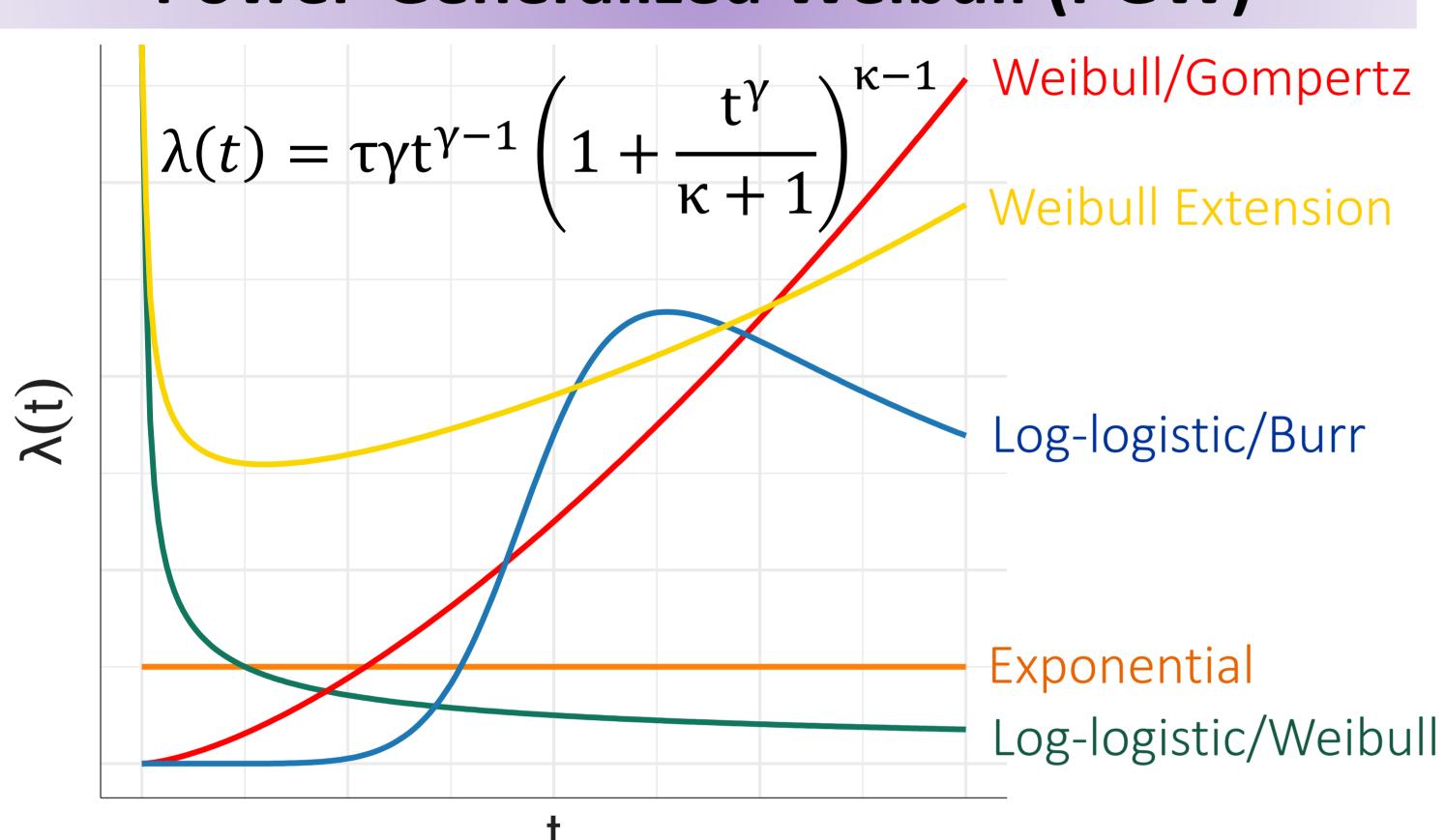


Figure 1. PGW hazard shapes.

## **Distributional Regression**

The PGW MPR model used in this research allows covariates to enter the hazard through the scale ( $\tau$ ) and shape ( $\gamma$ ) parameters where the additional shape ( $\kappa$ ) parameter is independent of covariates:

$$log(\tau) = x^T \beta$$
  $log(\gamma) = x^T \alpha$   $log(\kappa + 1) = \omega$  where  $x$  is the covariate vector and  $\beta$ ,  $\alpha$  and  $\omega$  are the regression coefficients associated with  $\tau$ ,  $\gamma$  and  $\kappa$ .

Scale:  $\tau>0\Rightarrow$  Magnitude of the hazard Shape:  $\gamma>0\Rightarrow$  Time evolution of the hazard Shape:  $\kappa>-1\Rightarrow$  Specifies the baseline distribution

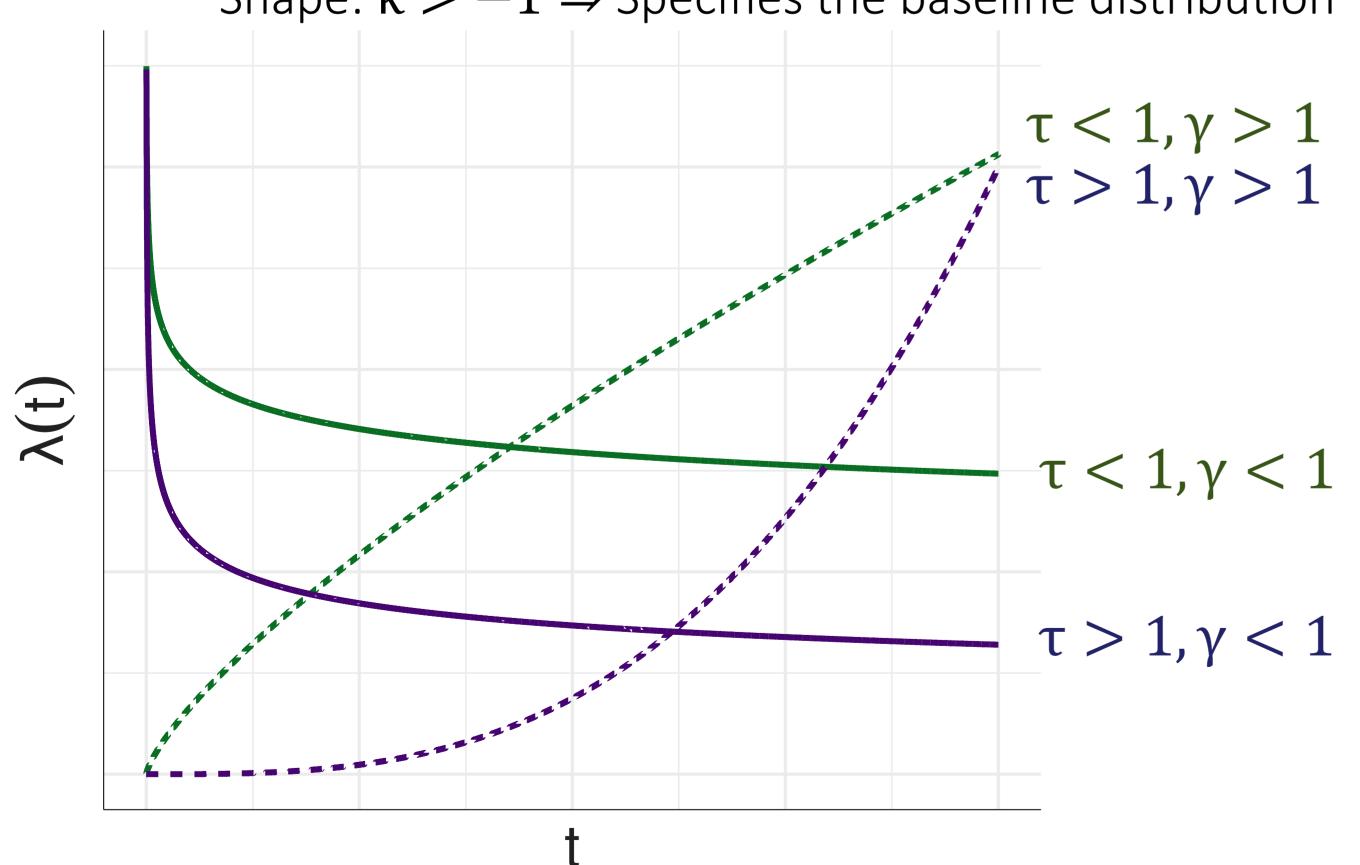


Figure 2. Impact of the shape  $(\gamma)$  and scale  $(\tau)$  on the hazard.

• Variable selection and parameter estimation are carried out using penalized regression (adaptive lasso penalty).

#### **Contact Details**



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## **Simulation Study**

	Scale (β)			Shape (α)		
n	C(7)	MSE	PT	C(7)	MSE	РТ
500	6.86	0.02	0.87	6.78	0.00	0.81
2000	6.95	0.00	0.96	6.96	0.00	0.96

**Table 1.** C, average correct zeros; MSE, average mean squared error; PT, probability of choosing the true model.

- The model performs well from a variable selection perspective where the average correct zeros is tending towards the oracle values as the sample size increases.
- Inference was also carried out which showed good performance.

## Data Application

- Veteran dataset Survival package in R
- Randomized trial of two treatment groups for lung cancer
- 137 observations

	PH	MPR
cell type: squamous	β	α
cell type: large	β	β
karno	β	α, β
Tuning Parameter	0.01706318	0.02833773
BIC	1466.42	1463.72

**Table 2.**  $\beta$  = "selected in scale",  $\alpha$  = "selected in shape", and those which are non-significant (at the 5% level) are shown in gray.

	Intercept	Large	Squamous	Karno					
β	-2.38	-0.42	<del>-</del>	-0.06					
α	0.59	_	-0.13	0.01					
ω	0.35	_	<del>-</del>	_					

**Table 4.** Coefficient estimation from MPR output where those which are non-significant (at the 5% level) are shown in gray.

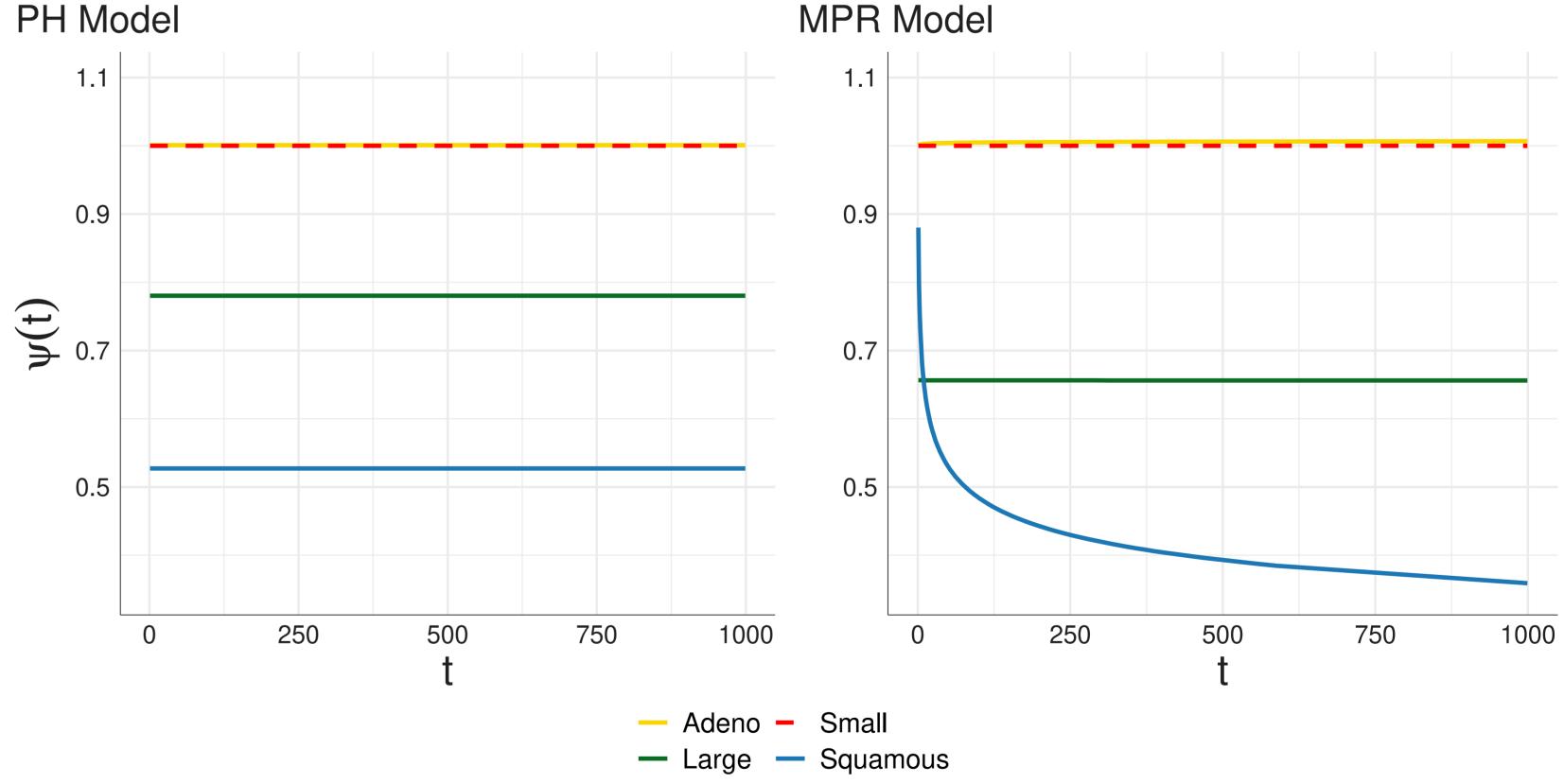


Figure 4. Cell type hazard ratios.

- Unlike PH models, MPR models allow for time-varying hazard ratios.
- This is the case for the squamous cell which has a smaller hazard relative to the reference category and this hazard is also decreasing over time

#### Conclusions

- Greater flexibility can be achieved by using an MPR model.
- Time-varying hazard ratios occur naturally by allowing the shape parameter to depend on covariates.
- Increased understanding of real-world data.

### References

- Burke et al. (2017). Multi-parameter regression survival modeling.
  Biometrics.
- Jaouimaa et al. (2019). Penalized Variable Selection in Multi-Parameter Regression Survival Modelling. arXiv:1907.01511.
- Burke et al. (2020). A flexible parametric modelling framework for survival