How to Use Survival Analytics to Predict Employee Turnover

(Or, Why You Shouldn't Use Logistic Regression to Predict Attrition)

Talent Analytics, Corp.

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May 16, 2017

Demo Code: https://github.com/talentanalytics/class_survival_101/

Who is Talent Analytics?

Predictive Modeling Platform – Advisor™

Talent Analytics

- We predict employee attrition and performance pre-hire.
- Much like credit risk modeling:
  - Predict likelihood to pay / default on mortgage, **before** extending credit
  - Predict likelihood to perform / leave role or company early, **before** extending job offer
- PAAS (Prediction As A Service)
- Seamless deployment of predictions into talent acquisition process

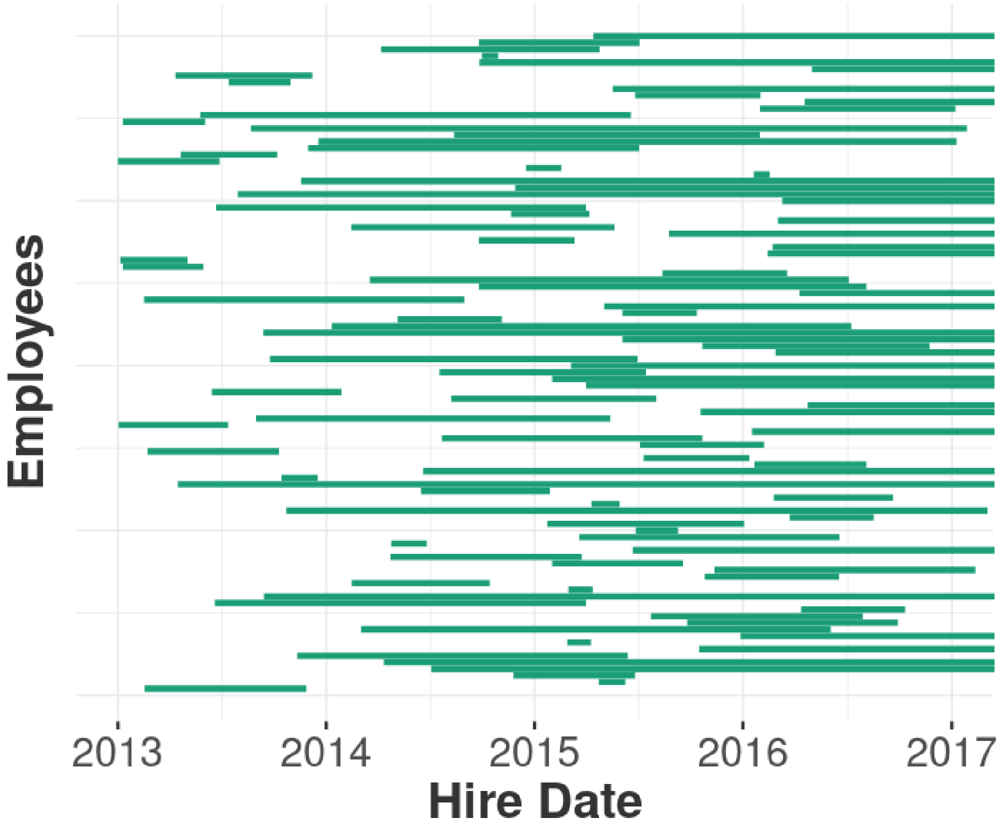
Turnover and Tenure:

A Timey-Wimey Relationship

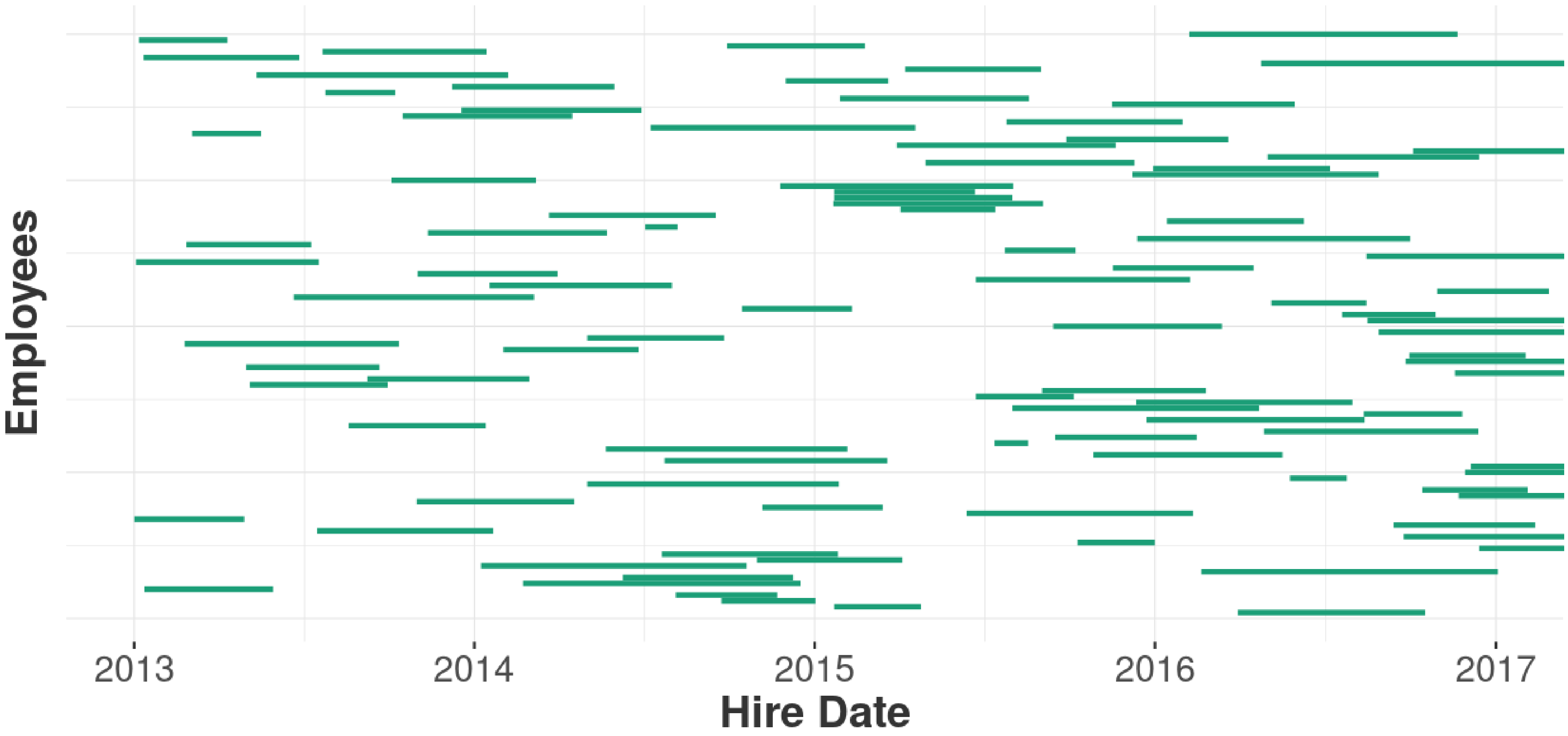
Two Different (But Related) Things

- **Turnover**: Percent of employees that terminate within a period of time
- **Tenure**: Employees' length of time working at a role or company

Is it a Wave or a Particle?

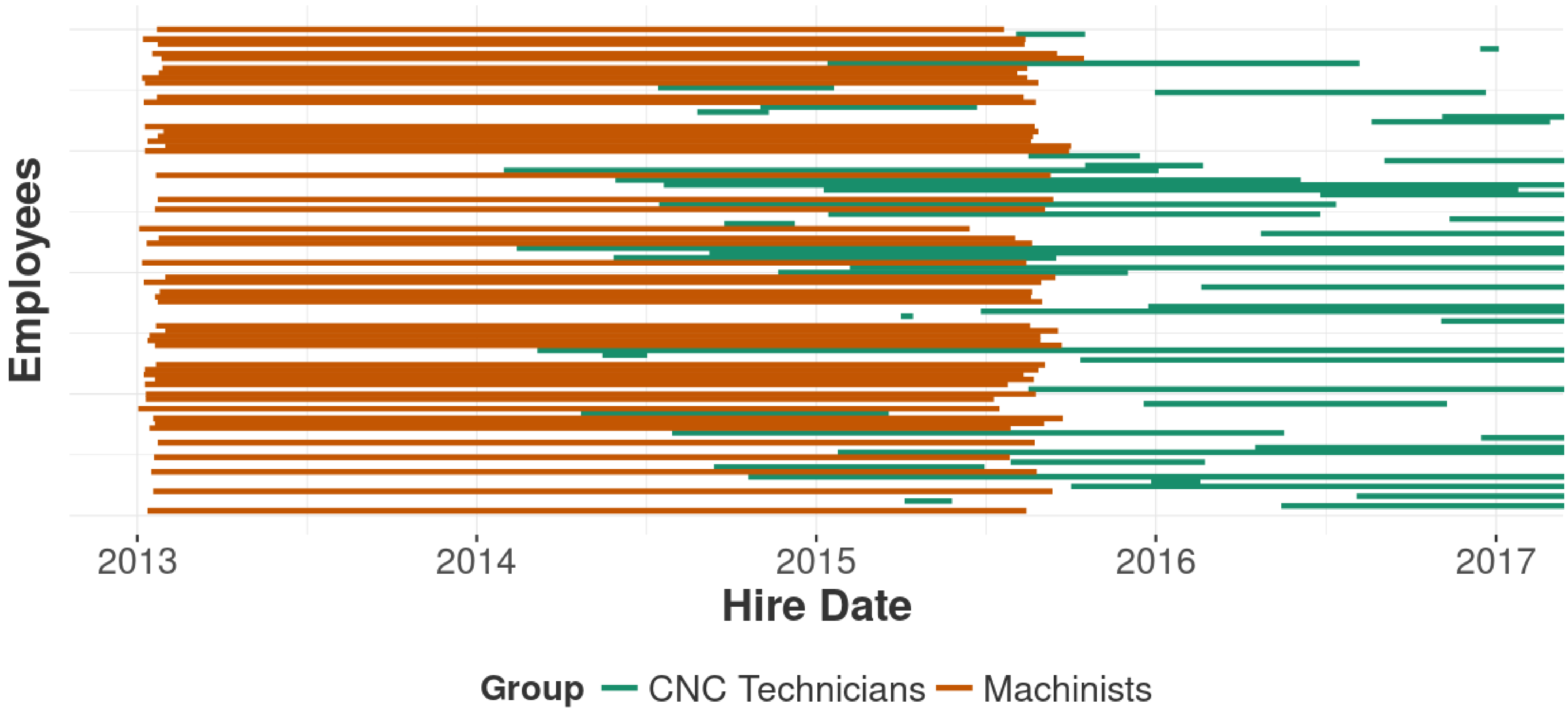


Low Tenure, High Turnover



High Tenure, Low Turnover

High Tenure, High Turnover (in 2015)

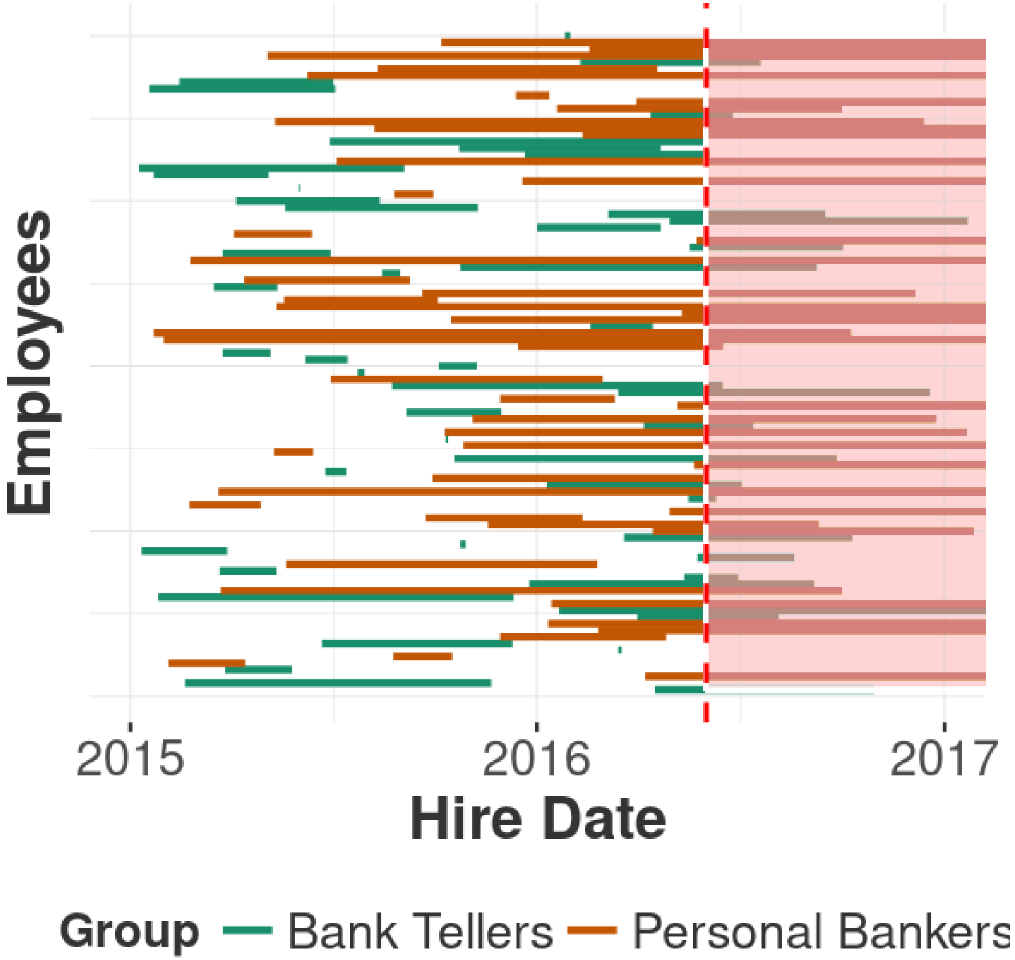


Low Tenure, Low Turnover (in Nov, Dec)

Main Problem: We Can't See the Future

- Everyone will terminate.
- Someday, somehow... But when?

- Technical Lingo: **Right Censoring**



Each Side Has Missing Information

Turnover Has No Information About Tenure

- Treats a temp the **same** as a seasoned veteran
- Ignores patterns - such as people quitting right after a bonus

Tenure Has No Information About Turnover

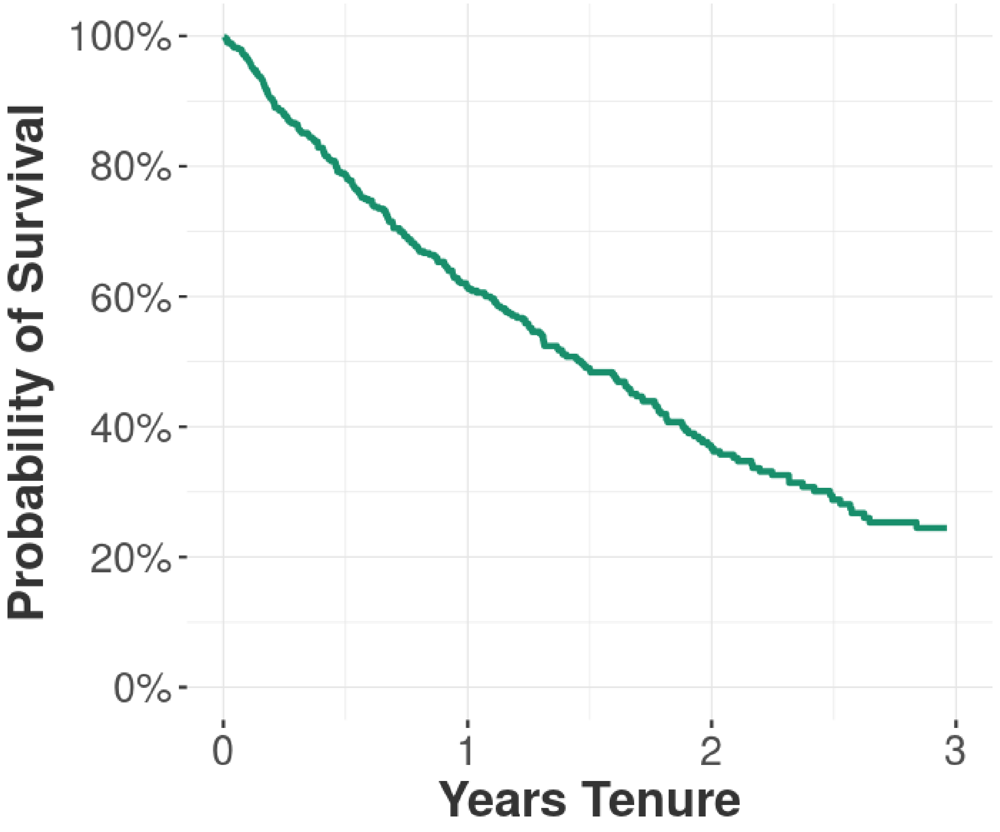
- High Tenure = staying power or retirement risk?

Each Side Varies Depending on When You Look

Annual Attrition Timing is Arbitrary

What if you could see attrition at every point in time?

- "One Year" only matters to accountants and astronomers
- Cumulative Breakeven matters more to the business



Survival 101

Survival Analytics

- **Medical Roots** - How long will a patient survive a disease?
- **Engineering Roots** - How long until a machine fails?
- **Social Science** - How long do people live?
- **Employment** - How long until an employee terminates? or promotes?

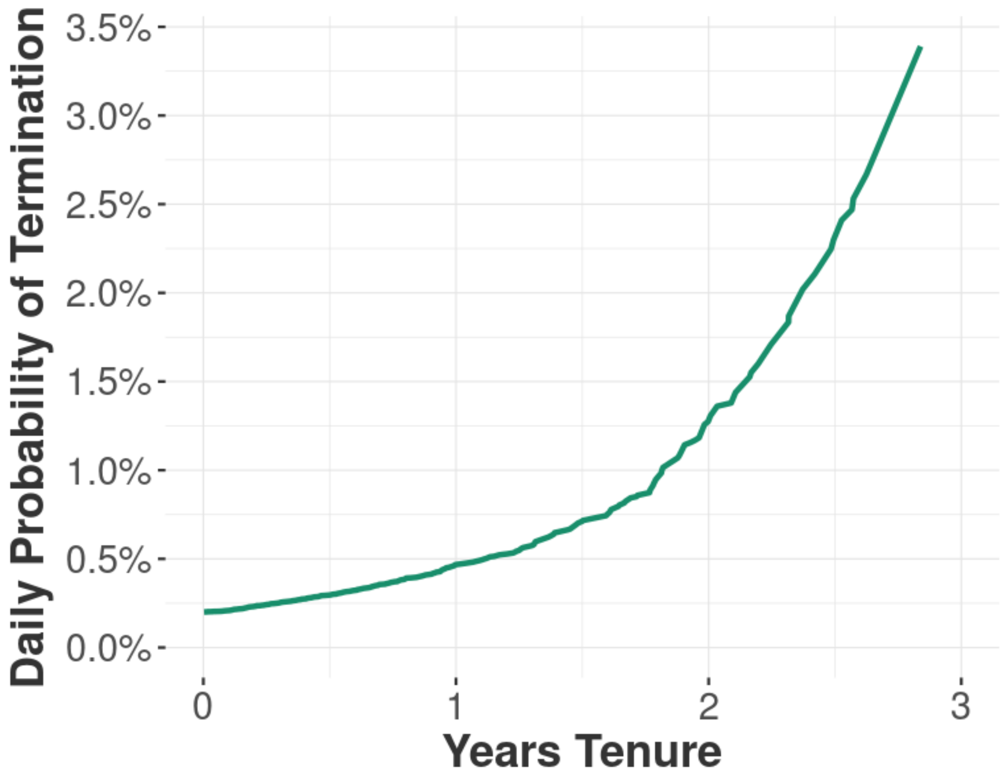
- **In General** - “Expected duration of time until one or more events happen”
- Artfully combines turnover and tenure

> Lots of competing jargon and syntax from many application domains:
> Failure Rate, Hazard Rate, Force of Mortality, ...

Hazard Rate:
Conditional Daily Risk of Termination

- Every day in tenure there is a (small) probability that the employee will terminate
- **Conditional on survival to the prior day**

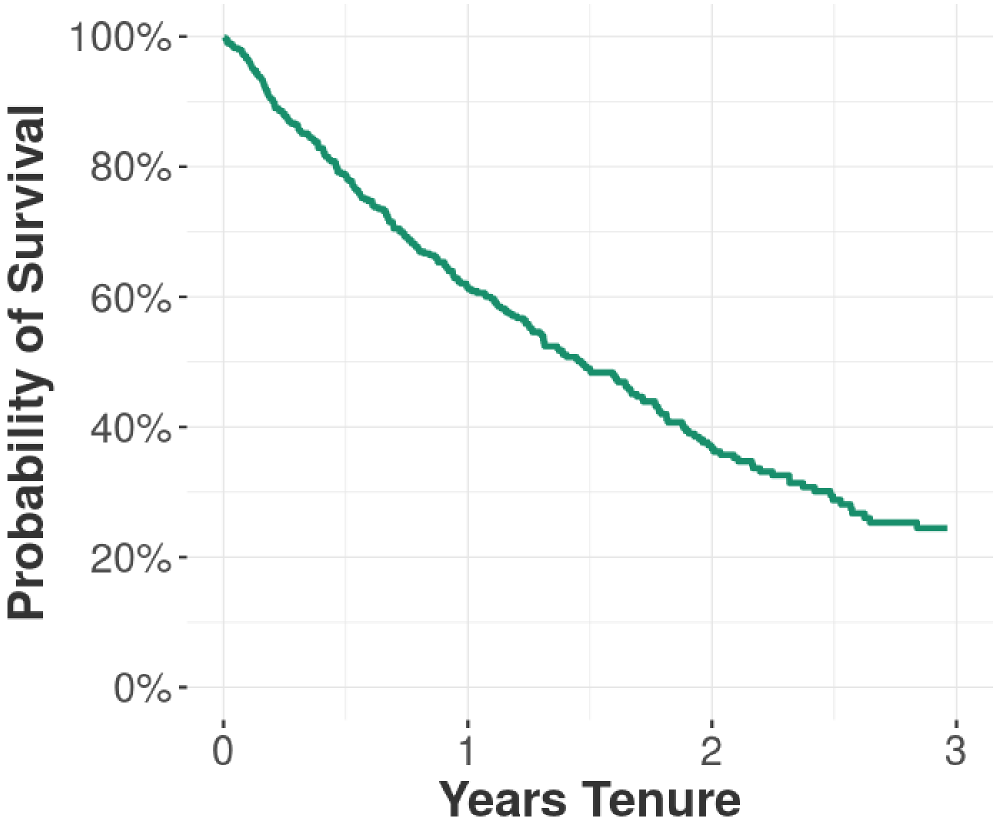
- Like an actuarial life table
- Can rise at different times:
  e.g. training, review or bonus time



Survival Rate: Daily Probability of Being Employed at Time *t*

- How likely are you to be working here, *t* days after being hired?

- Near 100% on Day 1 (some people actually never show up)
- Downhill from there - usually not linear
- One role at a time



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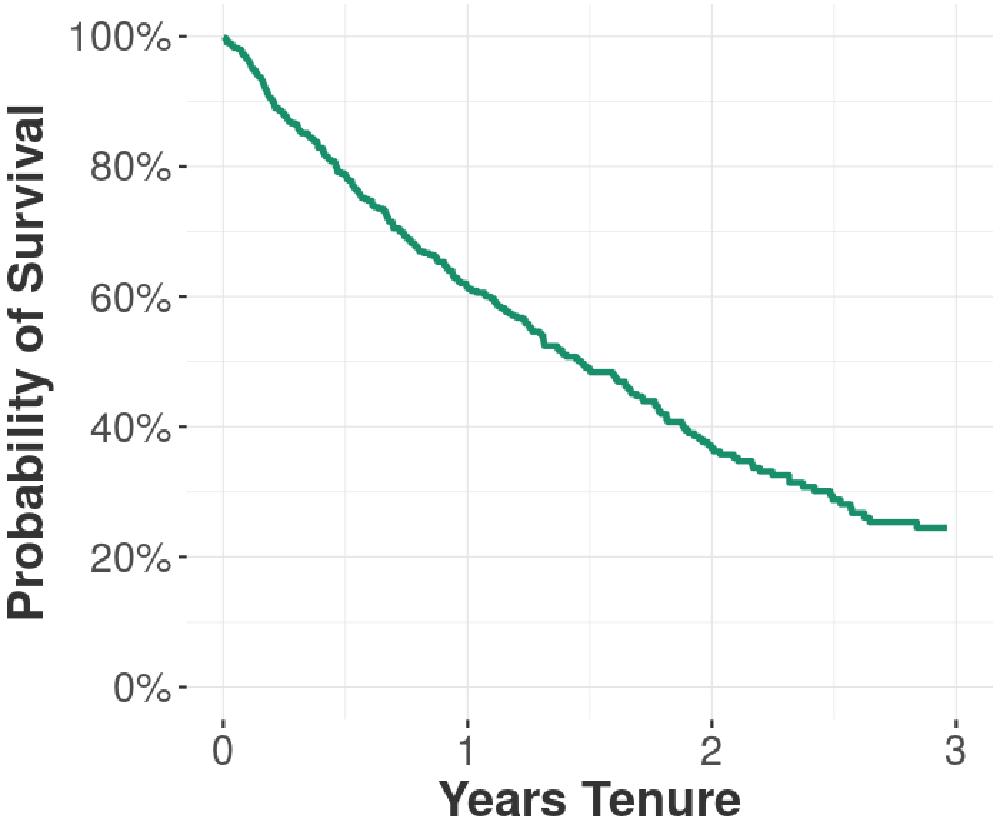
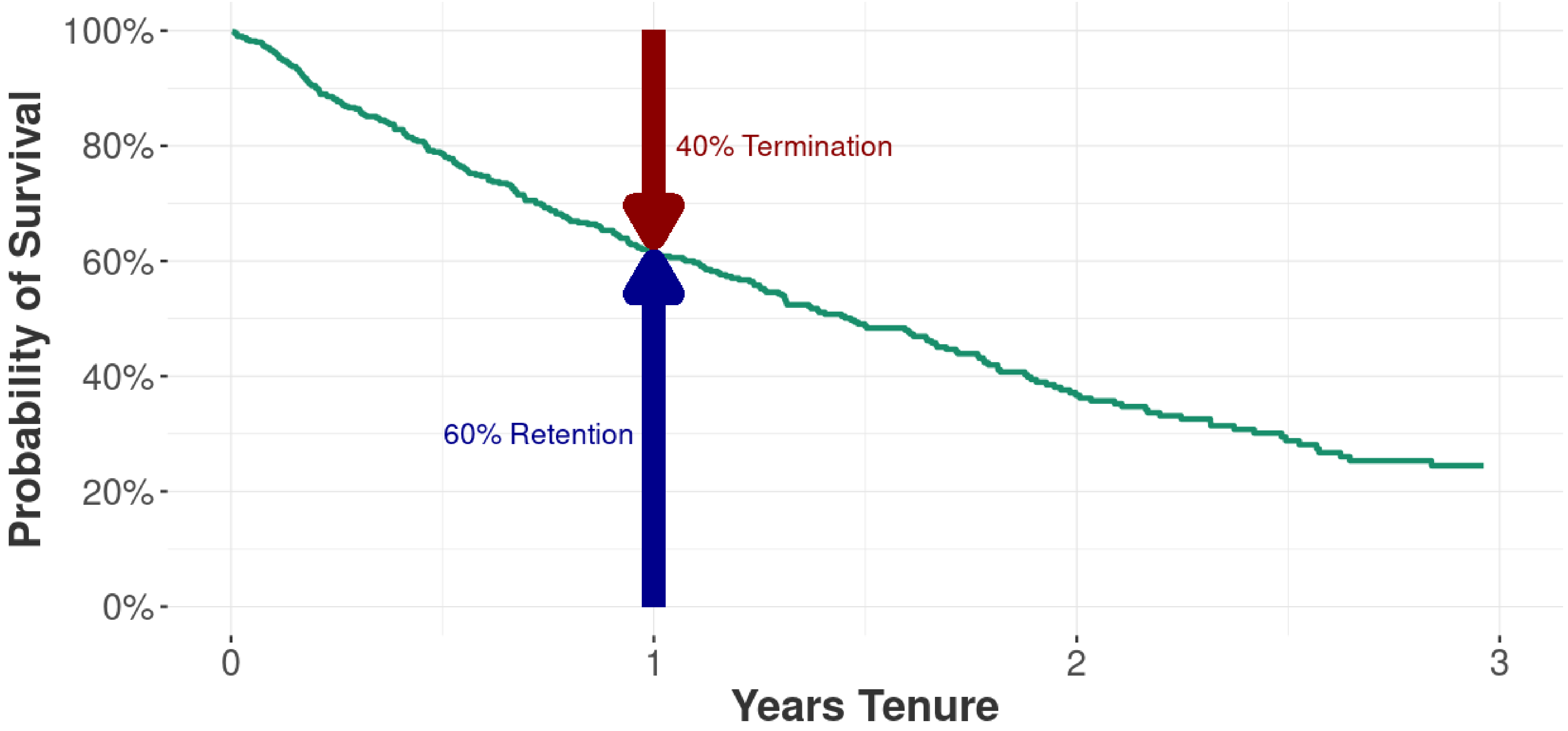
- *This* is the full picture

- Simple transformation of the Hazard Curve
  - Best to use statistical tool (R, SAS)
  - Apparently possible in Excel

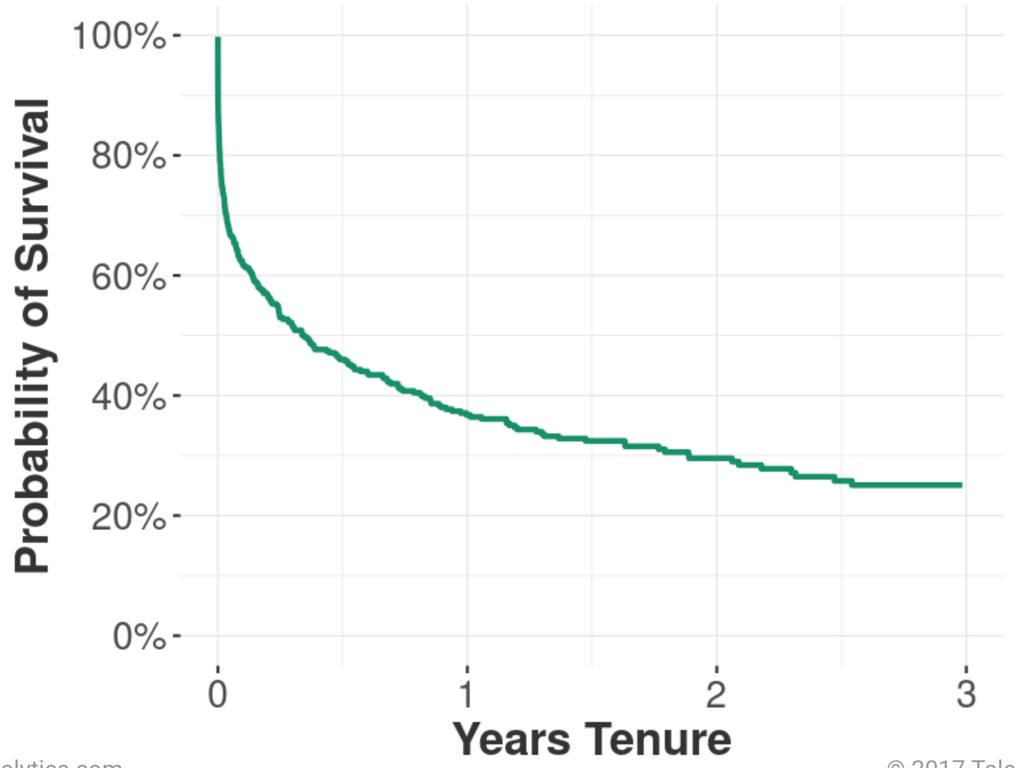


Attrition is Built Into Survival Curves

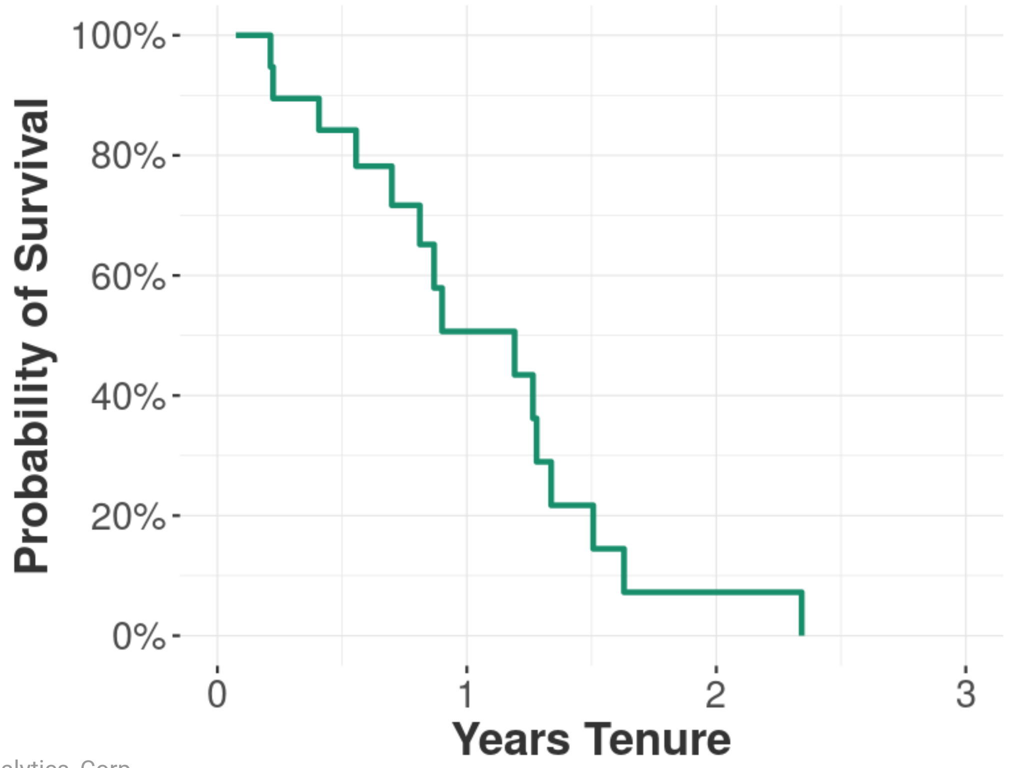


Many Shapes

Shelf Pattern

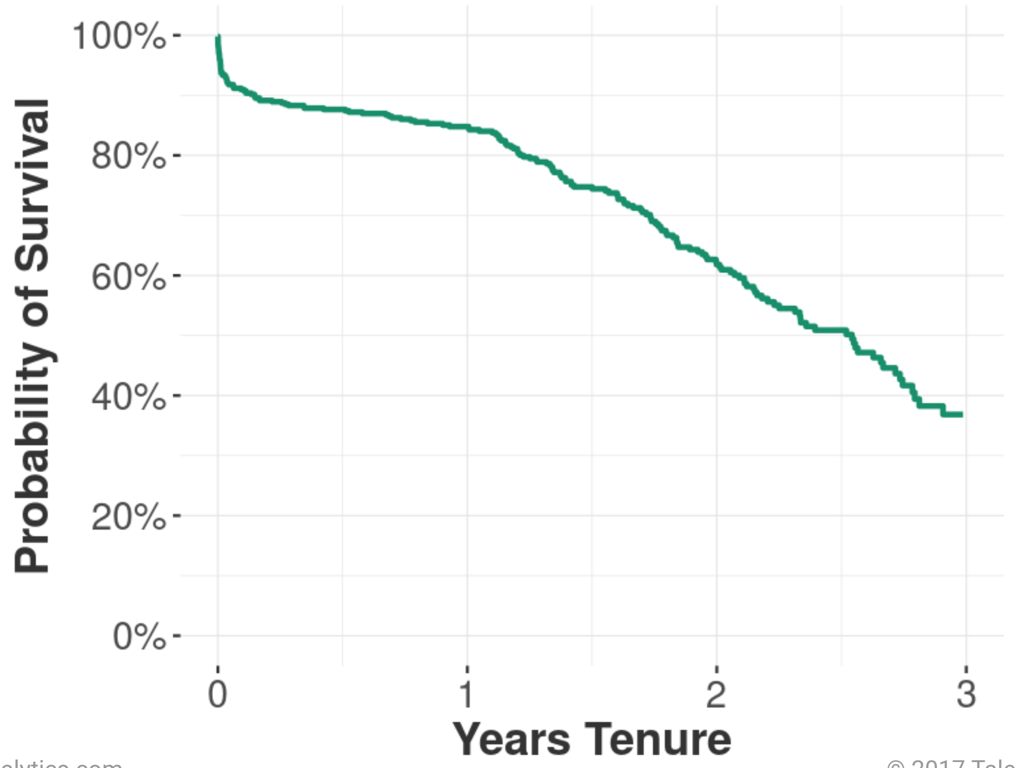


Sparse Pattern

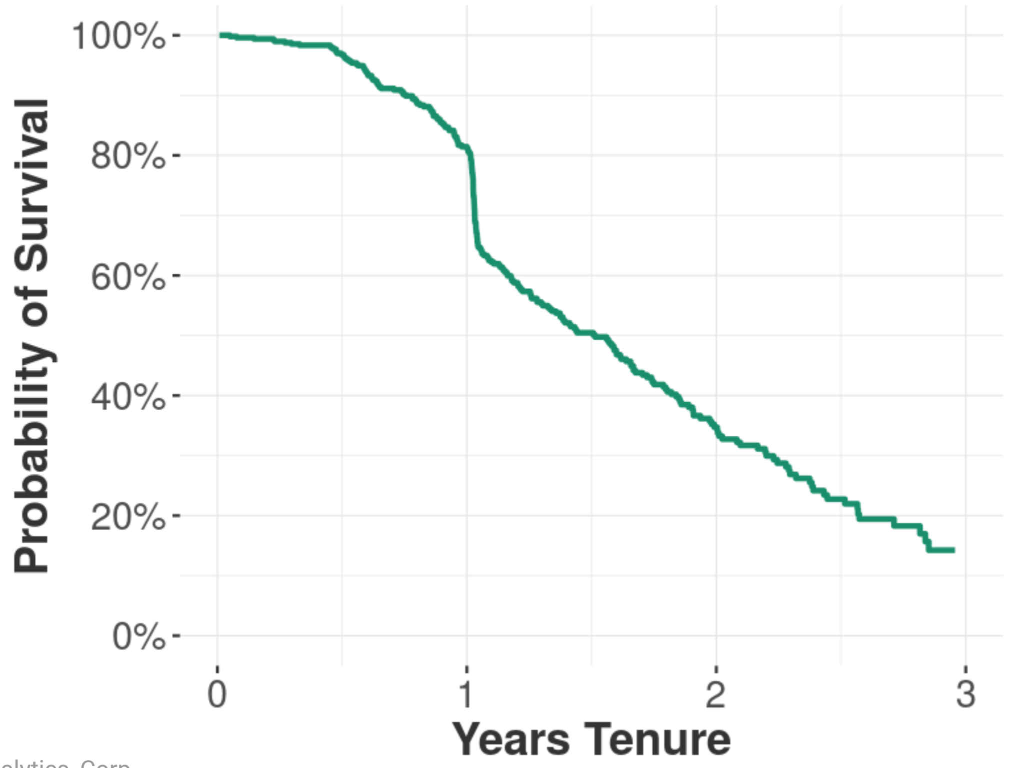


Cliffs or Kinks in the Survival Curve

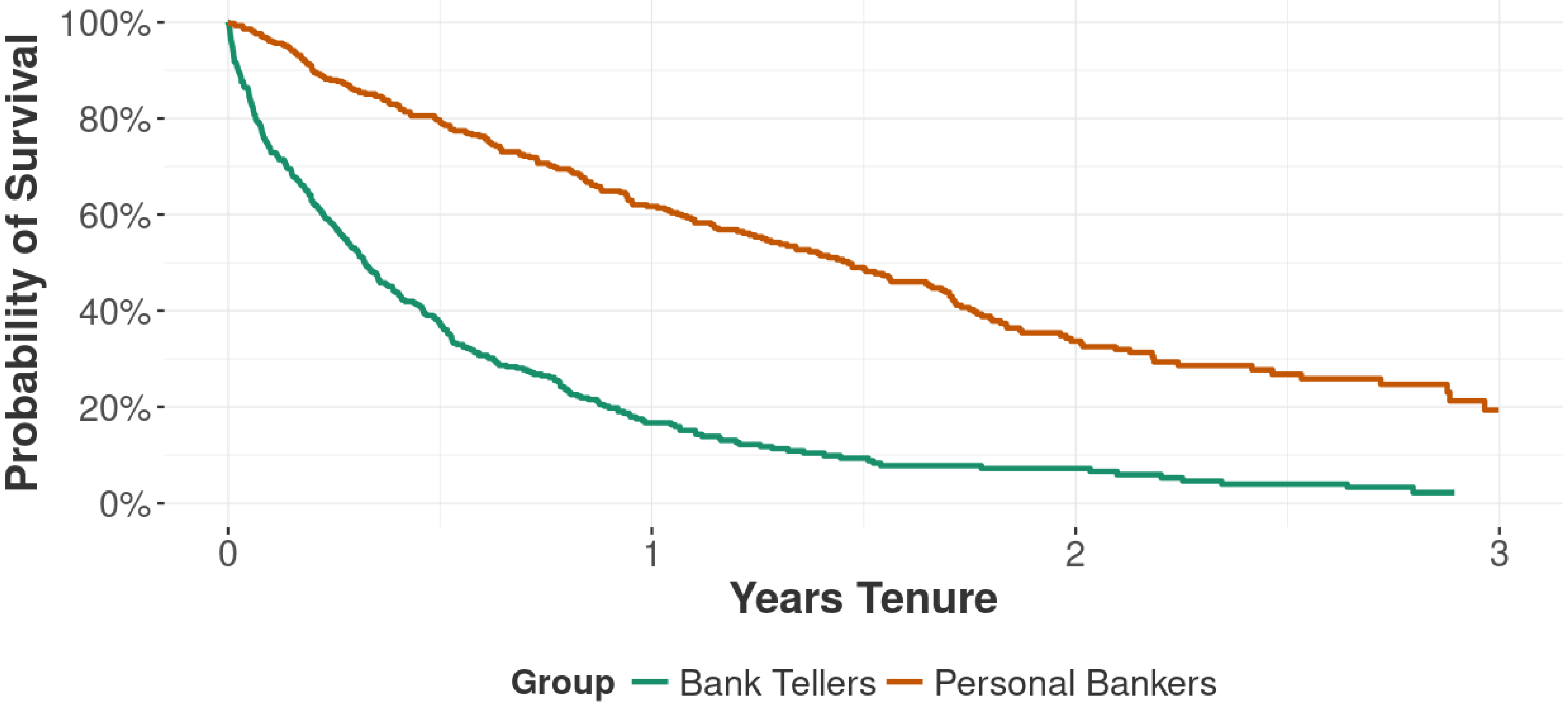
Heavy Terms During Training



Heavy Terms After 1-Year Bonus



Everyone Has a Survival Curve



Predicting Survival
To the Individual Employee

Don't Use Logistic Methods to Predict Attrition!

Commonly Done:

- Predict one-year attrition with logistic
- Use tenure as a variable along with others

Common Result:

- “The biggest cause of termination is tenure”
  - Not an actionable coefficient
- Ignores nuances available to survival methods
- Mishandles current employee tenure
- Less accurate

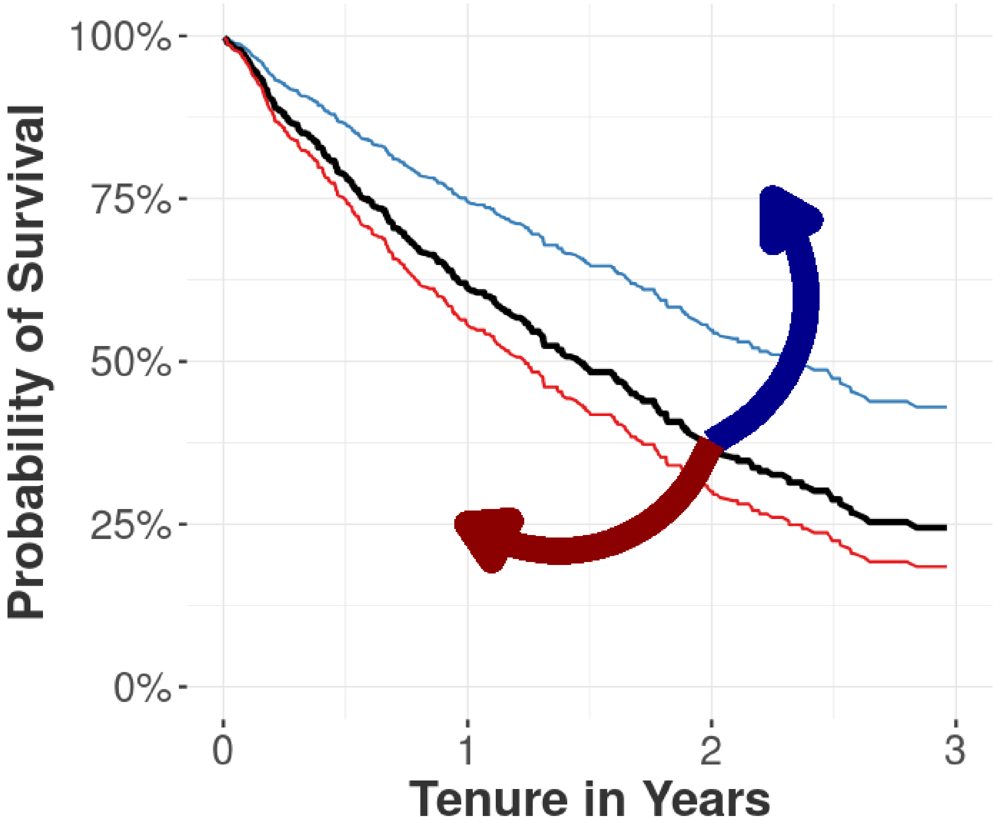
Proportional Hazard

Most Survival models are "Proportional Hazard"

- Start with Base Survival rate
- Convert to Base Cumulative Hazard rate

- Multiply Cumulative Hazard by a single factor (hence "Proportional Hazard")

- Linear changes to Hazard lead to a *rotation* of Survival Curve



Predictive Goal:

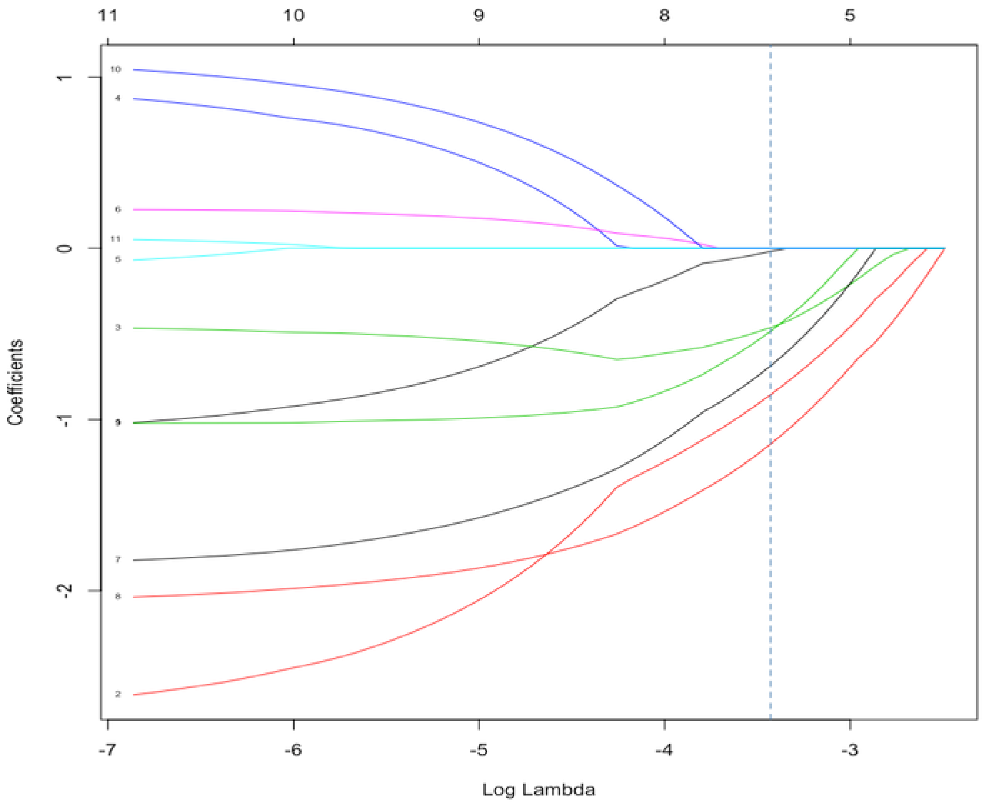
Predict the amount of Survival Curve rotation for each candidate

Proportional Hazard Prediction Methods

Predicting a Single Number

- Cox regression
  - Vanilla Cox
  - Stepwise
  - ElasticNet or LASSO
  - Variable selection with Random Forest
- Decision Trees
- Random Forests
- Neural Networks
- SVM, etc

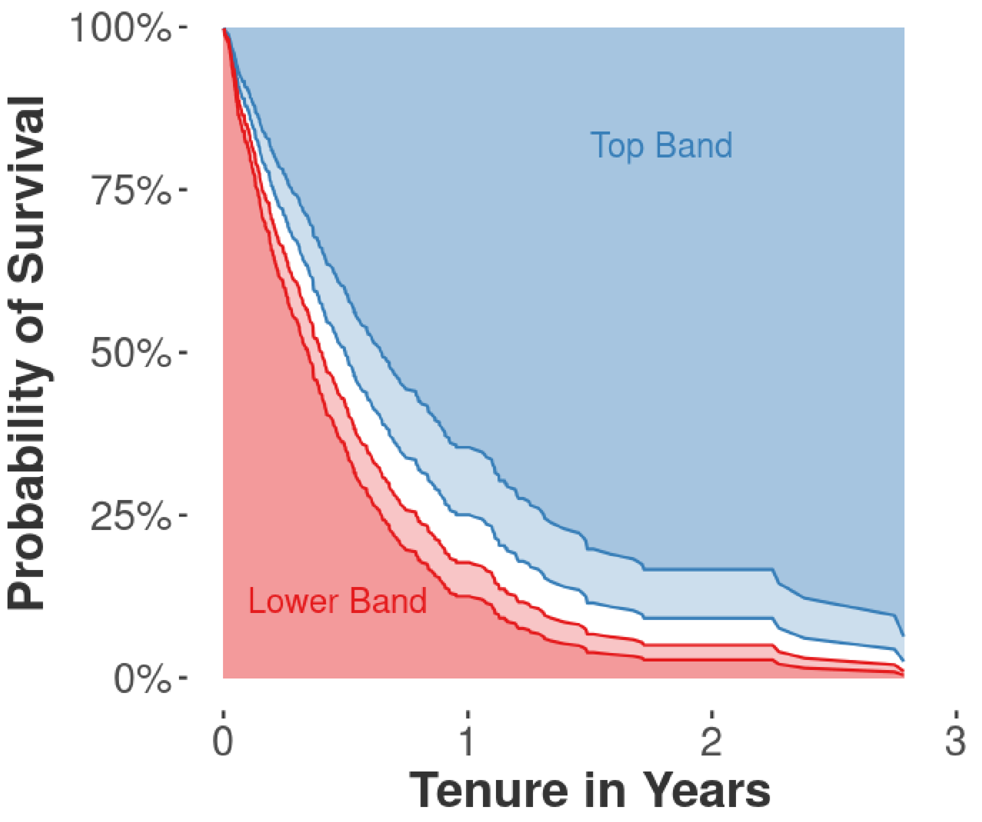
There are also other survival algorithms, including parametric methods



Build/Validate a Survival Model With Thresholds

The Model Predicts:

- ▶ “Dark Blue” hires will survive the longest
- ▶ “Light Blue” hires will survive above-median
- ▶ “Grey” survival curve is current median survival.
- ▶ “Light Red” and “Dark Red” candidates are not likely to survive.



Deeper Dive:

Predicting Survival with Proportional Hazard

Follow Demo Code on GitHub:

https://github.com/talentanalytics/class_survival_101/

Formulas and Jargon

Hazard Function: $h(t)$

- Probability of termination at time *t*, conditional on survival up to time t
- Ranges from 0 to 1 (typically very small)

Cumulative Hazard Function: $H(t) = \int_0^t h(x)\,\mathrm{d}x = -log(S(t))$

- Cumulative conditional probability of termination up to time t
- Ranges from 0 to 4ish (theoretically to Infinity)

Survival Function: $S(t) = e^{-H(t)}$

- Probability that termination will be later than time t
- Ranges from 1 to 0

Theoretically the formulas above are continuous measures, but in practice are discrete daily.

Calculating Survival in R

Four Simple Steps with R `survival` package:

1. Gather and Prepare the Data
2. Calculate Baseline Survival Function $S_0(t)$
3. Model Proportional Hazard with Cox Regression
4. Validate Model

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5. Deploy Model into hiring
6. Hire people likely to stay on the job longer
7. Save and earn money
   - Avoid attributing savings to soft factors like ripple effect, morale, engagement
   - Hard savings from reduced Replacement Cost
   - Hard earnings from increased Employee Lifetime Value

1) Gather Employee Data

```
> attr.data

  emp.id  hire.date  term.date   factor.x  factor.y factor.z
   <int>     <dttm>     <dttm>      <dbl>     <dbl>    <dbl>
1     52 2016-02-23       <NA> 0.09555369  1.515028 102.3811
2    261 2014-10-30       <NA> 2.40144024  9.065855 100.5727
3    193 2013-12-25 2015-03-28 1.88463382  4.331642 105.6887
4    150 2013-03-27 2013-09-19 3.81625316  7.363454 110.6842
5     31 2015-03-25       <NA> 5.17392728 11.824601 110.0590
```

Simple Requirements

- Just `hire.date` and `term.date` is all you need from HRIS
  - Leave `term.date` as `NA` if the employee haven't terminated yet

- Merge with predictive input (independent) variables
  - e.g. assessment results, experience, CV detail, social media, semantic
  - Here we use `factor.x`, `factor.y` and `factor.z`
  - Are these variables available pre-hire?

Calculate Fields for Survival

```
> attr.data %>% dplyr::select(-dplyr::contains("factor"))

  emp.id  hire.date  term.date is.term   end.date tenure.years
   <int>     <dttm>     <dttm>   <lgl>     <dttm>        <dbl>
1     52 2016-02-23       <NA>   FALSE 2017-05-01    1.1854894
2    261 2014-10-30       <NA>   FALSE 2017-05-01    2.5023956
3    193 2013-12-25 2015-03-28    TRUE 2015-03-28    1.2539357
4    150 2013-03-27 2013-09-19    TRUE 2013-09-19    0.4818617
5     31 2015-03-25       <NA>   FALSE 2017-05-01    2.1026694
```

Simple Derivations

- `is.term`: Have they terminated? Is `term.date` NA?
- `end.date`: Either `term.date`, or censor date, depending on `is.term`
  - Could put `transfer.date` here with no `is.term`
  - *The last date we know the employee was at work*
- `tenure.years`: What is employee tenure from `hire.date` to `end.date`?
  - *All we know about the employee's tenure, as of censor date*

Dataset is Ready

```
> glimpse(attr.data)

Observations: 400
Variables: 14
$ label       <fctr> a, a, a, a, a, a, a, a, a, a, a, a, a, a, a, a, a, a,...
$ hire.date   <dttm> 2013-04-20, 2016-01-14, 2013-09-20, 2014-05-17, 2016-...
$ term.date   <dttm> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, 2016-...
$ is.term     <lgl> FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, FALSE...
$ end.date    <dttm> 2017-05-01, 2017-05-01, 2017-05-01, 2017-05-01, 2017-...
$ tenure.years <dbl> 4.02975576, 1.29469635, 3.61029191, 2.95626651, 1.1463...
$ factor.x    <dbl> 7.44846858, 1.08376058, 2.81983987, 0.56880027, 0.7868...
$ factor.y    <dbl> 16.838313, 9.335225, 9.519951, 12.697147, 12.912898, 1...
$ factor.z    <dbl> 103.10732, 100.37171, 99.76382, 95.88645, 97.61509, 10...
$ emp.id      <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16,...
$ scale.x     <dbl> 2.41351313, -0.24754913, 0.47829958, -0.46285224, -0.3...
$ scale.y     <dbl> 1.31773198, -0.57718839, -0.53053544, 0.27187182, 0.32...
$ scale.z     <dbl> 0.3407242, -0.1849069, -0.3017096, -1.0467221, -0.7145...
$ is.training <lgl> TRUE, TRUE, TRUE, FALSE, FALSE, FALSE, TRUE, TRUE, TRU...
```

- Example is 400-row simulated dataset
- Scaled the input factors to consistent z-scale
- Separated into 80% training and 20% validation datasets

2) Calculate Baseline Survival ($S_0(t)$)

`survival::Surv` is a single object to hold Tenure and Turnover at once

```
> surv.obj <- survival::Surv(training.data$tenure.years, training.data$is.term)
```

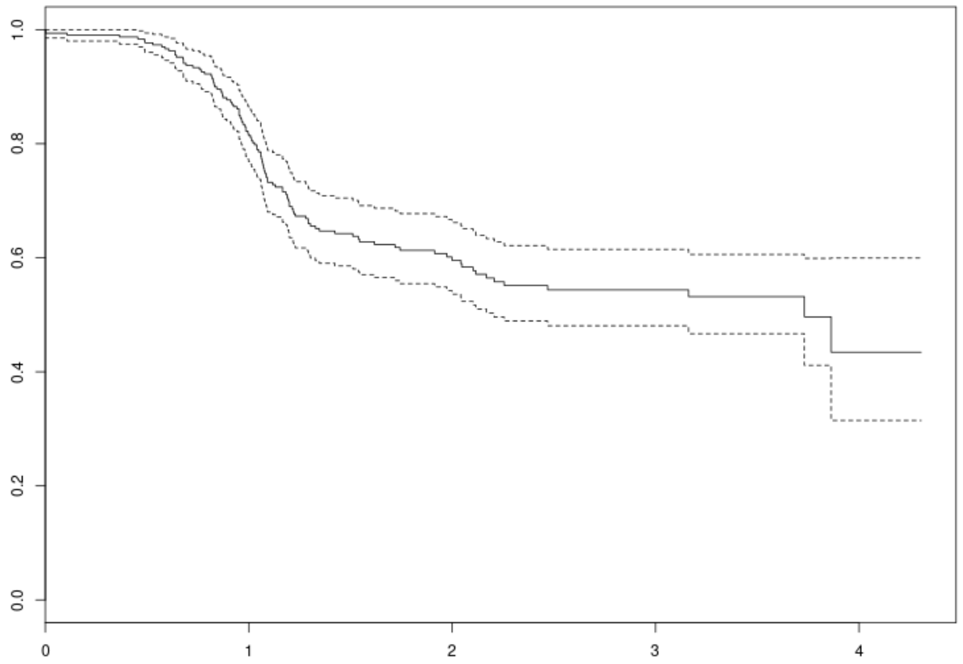
- Needs "time variable" `tenure.years` and "event variable" `is.term`

`survival::survfit` is the Kaplan-Meier Estimator of $S_0(t)$

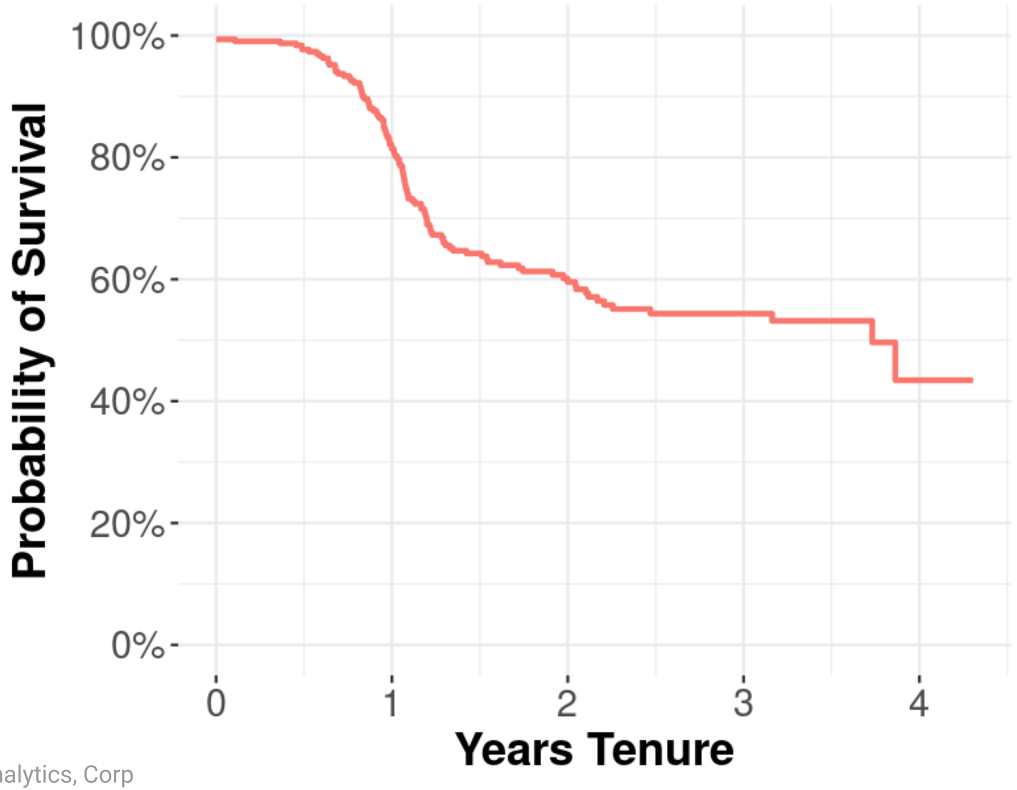
```
> surv.fit <- survival::survfit(surv.obj ~ 1)
> summary(surv.fit)
Call: survfit(formula = surv.obj ~ 1)

  time n.risk n.event survival std.err lower 95% CI upper 95% CI
 0.000    320       1    0.997 0.00312        0.991        1.000
 0.249    308       1    0.994 0.00448        0.985        1.000
 0.298    303       1    0.990 0.00554        0.980        1.000
 0.320    298       1    0.987 0.00644        0.974        1.000
```

Plot Baseline Survival

Native Survival Plot



Crafted ggplot2 Plot



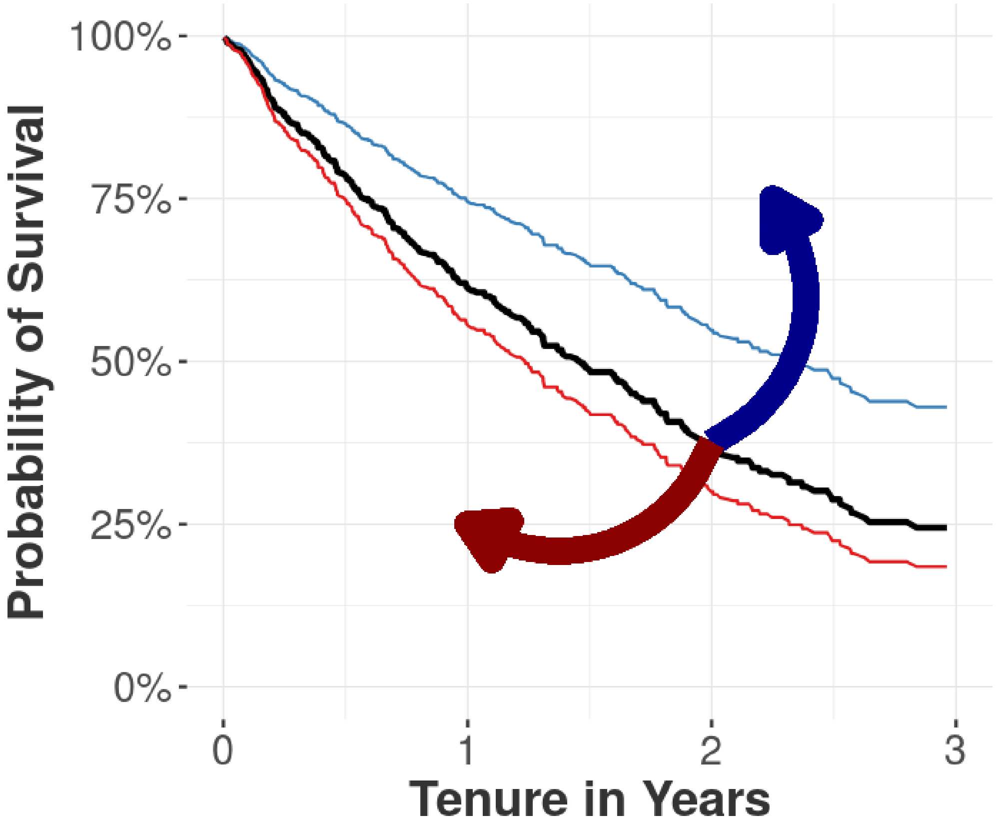
3) Back to Proportional Hazard

Consider a multiplier *x* that centers on 1

- Multiply $H_x(t) = H_0(t)x$
  for proportional (linear) changes to Hazard
- Survival Curve **rotates** in response:
  $S_x(t) = e^{-H_0(t)x}$

Beware - inverse relationship:

- $x \leftarrow 1.1$ will increase $H_x(t)$, decrease $S_x(t)$
- $x \leftarrow 0.9$ will decrease $H_x(t)$, increase $S_x(t)$



So we just need to predict *x* to predict Survival

- One number drives the entire curve, based on baseline $H_0(t)$

Model Proportional Hazard with Cox Regression

```
> cox.model <- survival::coxph(formula = surv.obj ~ scale.x + scale.y + scale.z,
                               data = training.data)

> cox.model

Call:
survival::coxph(formula = surv.obj ~ scale.x + scale.y + scale.z,
    data = training.data)

           coef exp(coef) se(coef)     z         p
scale.x -0.4298    0.6506   0.0918 -4.68 0.0000028
scale.y -0.3204    0.7258   0.0957 -3.35   0.00082
scale.z -0.1967    0.8215   0.0984 -2.00   0.04558

Likelihood ratio test=38.2  on 3 df, p=0.000000025
n= 320, number of events= 125
```

4) Predict `validation.data` with New Cox Model

```
> cox.pred <- predict(cox.model, newdata = validation.data, type = "lp")
```

- Note: we built model with `training.data`, now we predict against `validation.data`
  - Our model has never seen anything in `validation.data`
  - Great test to see how closely our predictions match known outcomes

- The `predict.coxph()` function returns 5 different types of predictions
  - We want `type = "lp"` which is `log(multiplier)` to baseline $H_0(t)$
  - Other types won't work with `survivalROC()`

How does ROC Work with Survival?

```
> roc.obj <- survivalROC::survivalROC(Stime = validation.data$tenure.years,
                                      status = validation.data$is.term,
                                      marker = cox.pred,
                                      predict.time = 1,
                                      lambda = 0.003)

> roc.obj$AUC
[1] 0.7102442
```

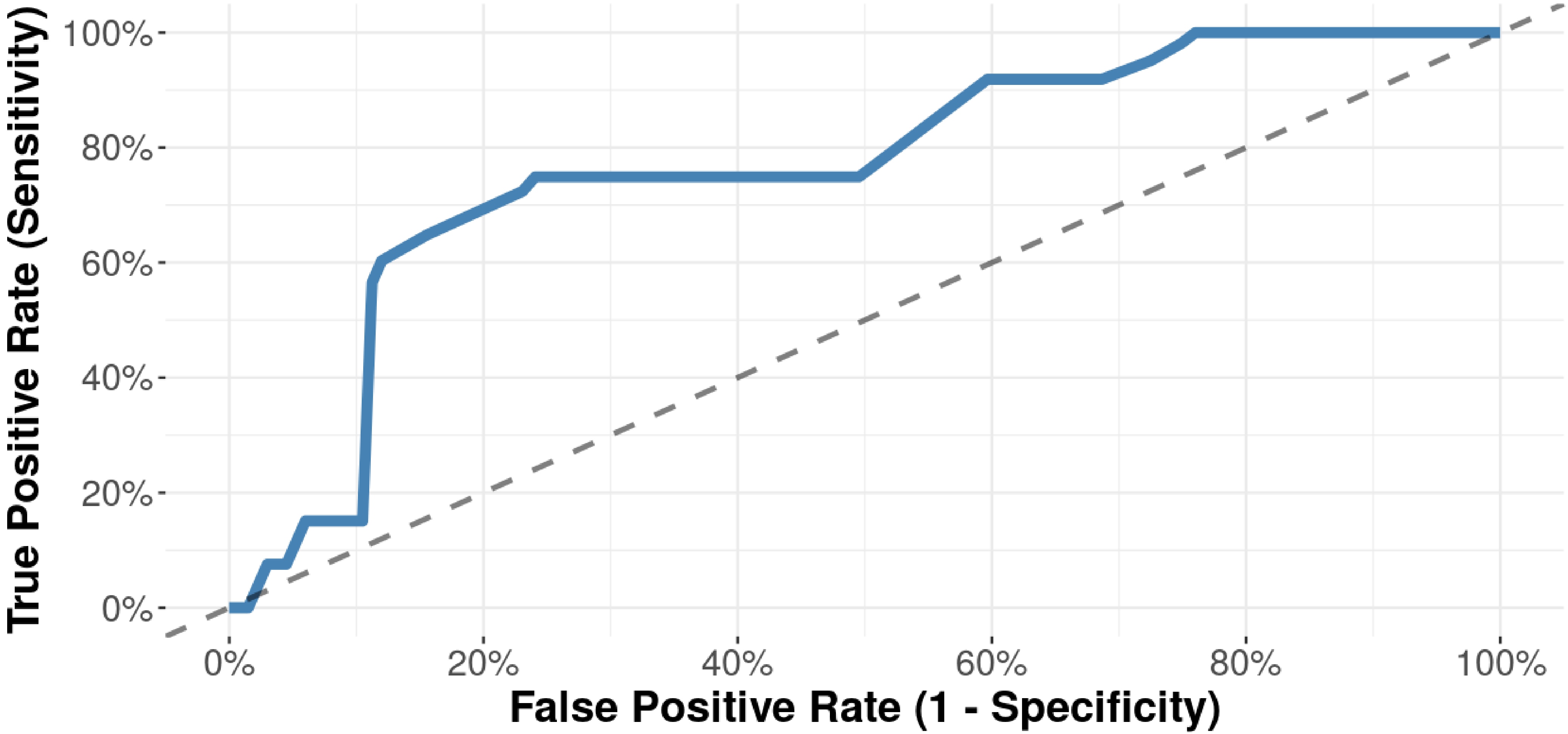
ROC typically evaluates classification methods

- So, we make this a classification problem
- **Classify:** Was the employee terminated at `t = 1` or not?
- Compare actual vs. predicted classifications at all cutpoints

Our AUC is 0.71

- Not bad for a censored attrition prediction!

Plot AUC with ggplot2



Don't Get Fooled by Randomness

We are predicting AUC, too

- Let's try predicting 1000 random samples of the same underlying pattern

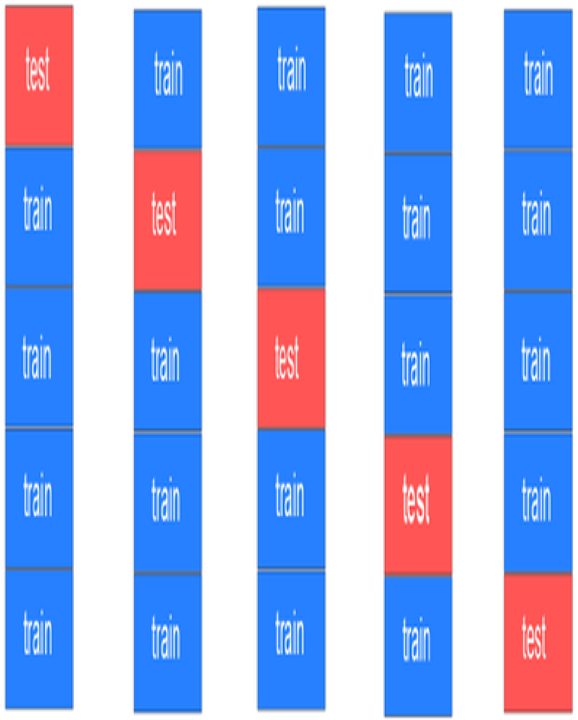
```
> test.repl <- replicate(1000, demoPrediction(verbose = FALSE))

> summary(test.repl)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 0.3470  0.6191  0.6833  0.6771  0.7356  0.9446
```

- AUC generally fell between 0.619 and 0.735, but 50% were outside this range
- The likely AUC is closer to 0.68 - still good
- What if you got a **lucky** (or unlucky) 80/20 validation split?

Multiple Cross-Validation

Raises the Bar
Against Getting Fooled

- Typically run 20-100 CV iterations
- Can consume lots of core-hours if nested for hyperparameters



Download and Experiment With this Code

- Download demo code and doc from
  https://github.com/talentanalytics/class_survival_101/

- Clone it, fork it, run it
- Send bug fixes
- Let me know how it goes

Questions and Discussion

Pasha Roberts

pasha@talentanalytics.com

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