INSTITUTE FOR DEFENSE ANALYSES

Forecasting Competing Risks for Navy Personnel Management

WEAI 2021

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Executive Summary

To better leverage its wealth of personnel data to achieve a high-quality fighting force, the Assistant Secretary of the Navy, Manpower and Reserve Affairs (ASN M&RA) collaborated with the Institute for Defense Analyses (IDA) to produce high-fidelity predictions regarding retention decisions—including the manner of exit—at the level of the individual sailor. To this end, we expand IDA's time-to-event prediction capability tool, the Finite Interval Forecasting Engine, to accommodate different types of exit to estimate the likelihood that a person exits into each of a finite number of discrete states in some given future period. We demonstrate this capability by predicting the manner of exit for a group of enlisted service members in the U.S. Navy.

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Manner of exit informs current force trajectories and how to target retention efforts

Early interventions can steer individuals toward further service or more favorable exit conditions

The same methodology can be used to model career trajectories

We use a competing risks framework to forecast the probability of exit into one of many states

Source: https://www.navytimes.com/news/your-navy/2020/04/17/heres-how-the-navy-is-ramping-up-its-reenlistment-bonus-policy-to-retain-sailors/

Expansion of IDA capabilities

IDA's Finite Interval Forecasting Engine (FIFE) was designed to forecast when an individual leaves service

We expand the FIFE to forecast how an individual leaves service conditional on leaving and incorporate this into a competing risks framework

We'll talk about the performance of this expansion and an application to Enlisted Navy Personnel

https://github.com/IDA-HumanCapital/fife

Extending the Finite Interval Forecasting Engine (FIFE) for Competing Risks

A competing risks framework models the occurrence of many different manners of exit

Without competing risks:
Probability of Exit at Time t

$Pr(T \leq t)$	2021	2022	2023
Leave	0.1	0.3	0.8
Stay in	0.9	0.7	0.2

With competing risks:
Probability of Exit at Time t by manner d

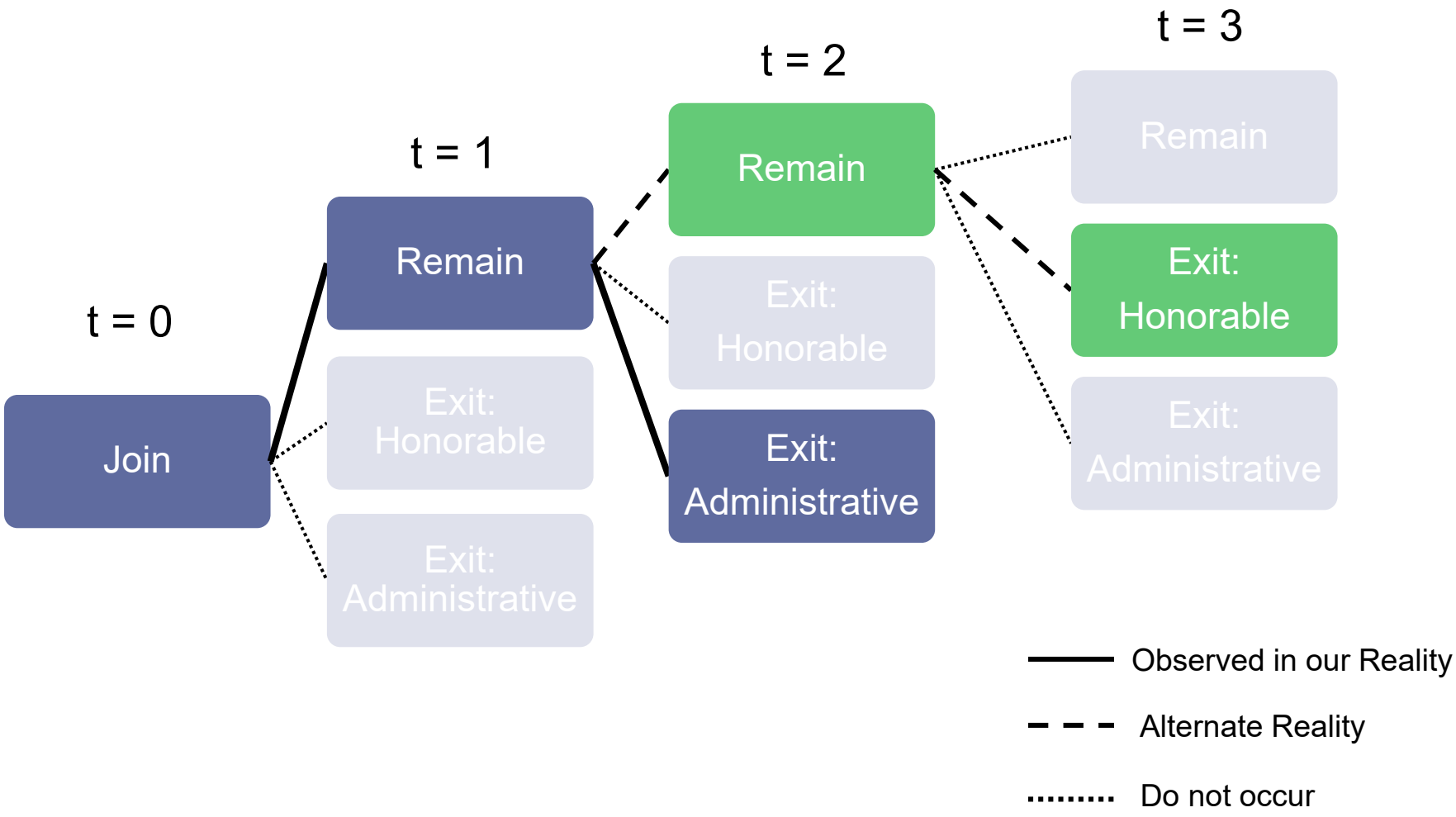
$Pr(T \leq t \text{ and } D = d)$	2021	2022	2023
Honorable	0.0	0.0	0.4
Administrative	0.1	0.2	0.3
Dishonorable	0.0	0.0	0.0
Medical	0.0	0.1	0.1
Stay in	0.9	0.7	0.2

Competing risks expands the resolution of force trajectories from *when* to *how* individuals attrite

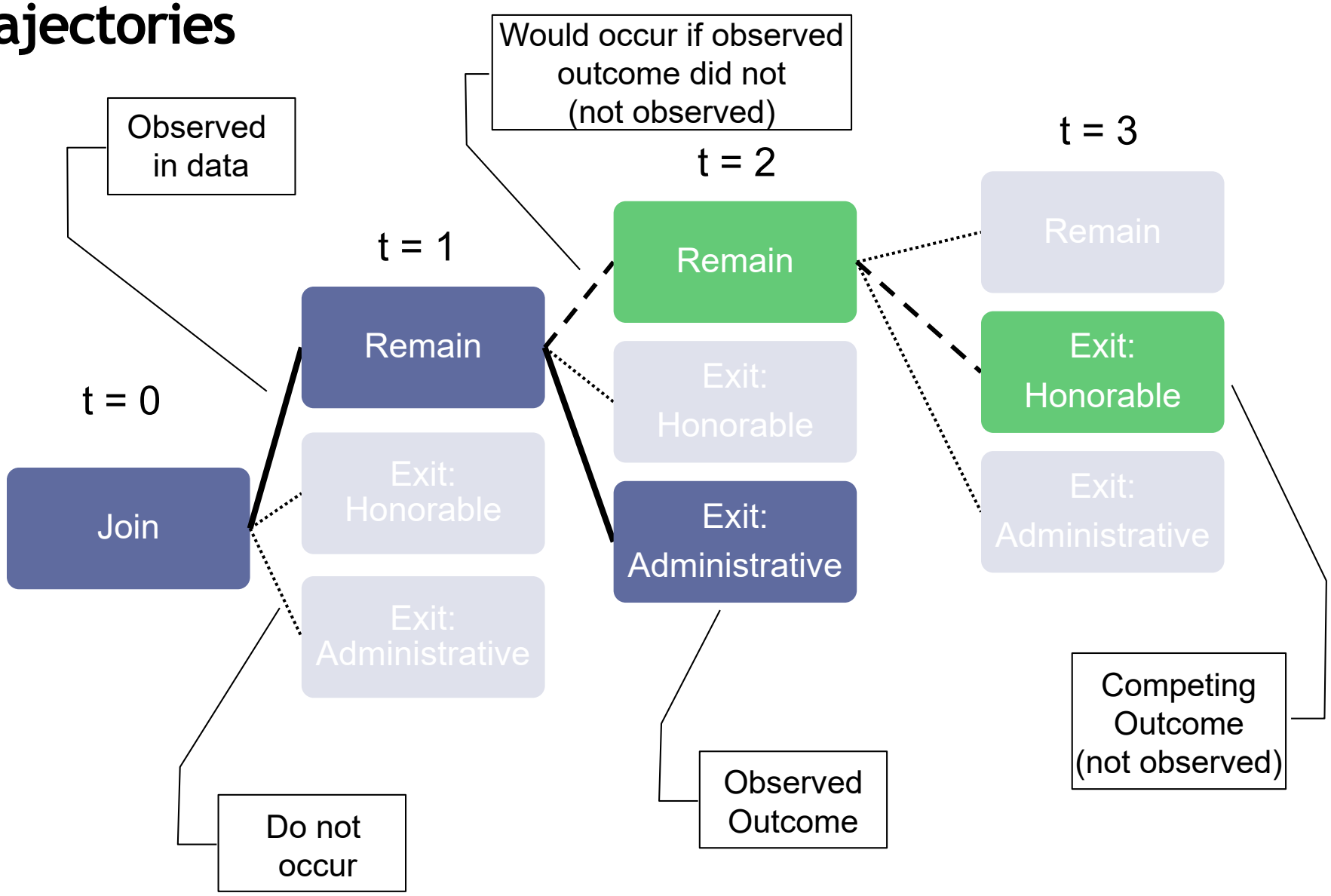
It can also be used to predict any set of mutually exclusive outcomes…

Such as exit into other ratings/designators, components, positions, etc.

Example: Competing risks in individual career trajectories



Example: Competing risks in individual career trajectories



Competing Risks

There are K mutually exclusive outcomes

Each outcome occurs at time T_{ik} for $k = 1,2, \dots, K$

Right Censoring occurs at T_{i0} (no outcome observed)

We only observe the outcome that occurs first (or censoring) and the associated time:

$$\mathrm{d}_i = argmin\{T_{i0}, T_{i1}, \dots, T_{iK}\} \text{ and } \mathrm{T}_i = \min\{T_{i0}, T_{i1}, \dots, T_{iK}\}$$

If event k occurs at time $T_i = T_{ik}$, then a different event could eventually occur had event k not occurred.

Forecasting the Cause-Specific Hazard

The cause-specific hazard estimates the probability* of exiting at time t in manner d

$$\mathrm{P}(T = t \text{ and } D = d | T \geq t, X_t) = \mathrm{P}(D = d | T = t, X_t)\, \mathrm{P}(T = t | T \geq t, X_t)$$

FIFE models the probabilities of exit and manner of exit separately

$$\mathrm{P}(T = t | T \geq t, X_t) = 1 - \frac{1}{1 + \exp\{-f_t(X_t)\}}$$

$$\mathrm{P}(D = d | T = t, X_t) = \frac{\exp\{-g_{dt}(X_t)\}}{\sum_{m=1}^{K} \exp\{-g_{mt}(X_t)\}}$$

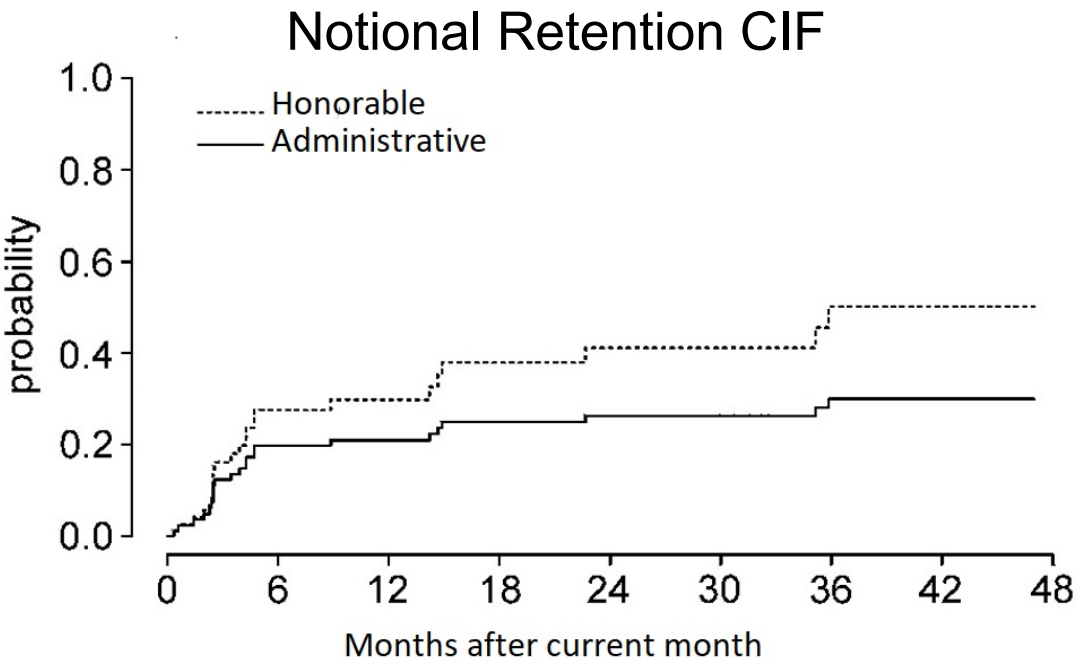
Estimation of f and g uses a tree based modeler

*also conditional on non-censoring

The Cumulative Incidence Function helps visualize this probability over time

Define $\tilde{T} = T - T_0$ as the time after censoring.

$$\mathrm{P}(0 < \tilde{T} \leq t, D = d | \tilde{T} \geq 0, X_t) = \sum_{k=1}^{t} \mathrm{P}\left(\tilde{T} = k, D = d \middle| \tilde{T} \geq 0, X_t\right)$$



Performance
under controlled conditions

Simulation Experiment Setup

Sample Data

ID	Period	X_1	X_2	X_3	Exit Type
0	39	B	0.068	0.392	No_exit
0	40	B	0.281	0.492	No_exit
1	7	C	-0.569	0.660	X
1	8	C	0.456	0.860	X
1	9	C	-0.155	1.060	X
1	10	C	1.106	1.260	X
1	11	C	-0.535	1.460	X

This illustrative data generating process (DGP) is simple:

- Only X_1 is predictive of Exit Type. $X_1 \in \{A, B, C\}$
- Probability of exit is fixed in a given period
- Exit Type $\in \{No\ Exit, X, Y, Z\}$

Simulation Experiment Setup

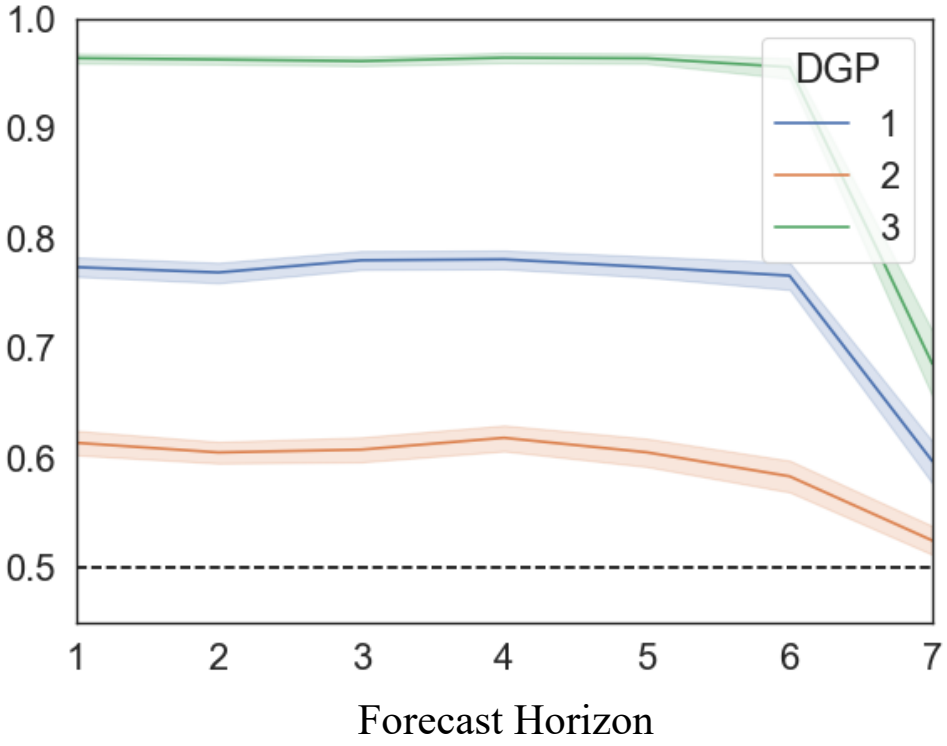
Expected Predictivity:

Medium				Low				High			
DGP 1				DGP 2				DGP 3			
	P(exit type)				P(exit type)				P(exit type)		
X_1	X	Y	Z	X_1	X	Y	Z	X_1	X	Y	Z
A	0.7	0.2	0.1	A	0.7	0.2	0.1	A	0.95	0.025	0.025
B	0.2	0.7	0.1	B	0.33	0.33	0.33	B	0.025	0.95	0.025
C	0.1	0.2	0.7	C	0.33	0.33	0.33	C	0.025	0.025	0.95

An individual with $X_1 = A$ is more likely to exit into state X, etc.

X_1 is most predictive of exit type for DGP 3 and least predictive for DGP 2

Performance – AUROC*



Probability of exit = 20% in a given period

N=1000

Censoring at 20 periods

1000 simulations

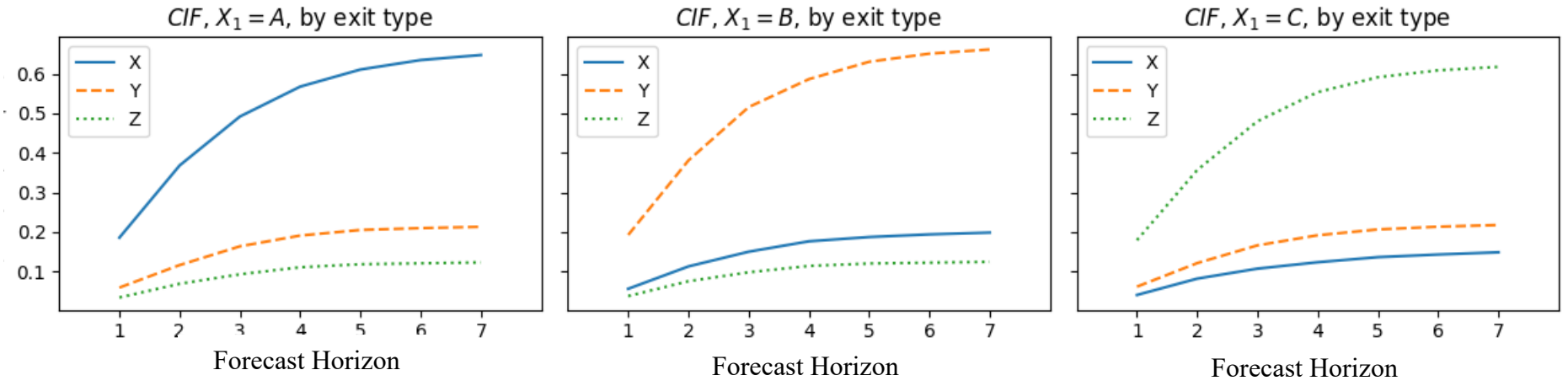
Shaded area is 95% confidence interval (MC)

Better performance for shorter forecast horizons, when more data is available, and when the covariates are more predictive of the outcome

Other specifications provide similar results

* Area Under the Receiver Operating Characteristic curve (AUROC)

Cumulative Incidence Functions



N=10000, censoring is at 20 periods, probability of exit is fixed at 50% per period

Probability of exit into each exit category grows with the forecast horizon

Ranking of exit type probabilities by group is correctly captured

CIFs approach the estimated probabilities of exit type conditional on exit

Application

Application – Overview

Item	Details
Source	DMDC Active Duty Master
Population	AD Navy Enlisted
Time Period	2015 - 2020, Monthly
Sample	20%
N	93984
N_{censored}	59050
Observation Count	3995318

Predictors come from DMDC and other sources:

- Demographics,
- Family characteristics,
- Service Retention Bonus eligibility,
- Time to end of contract,
- Economic conditions
- and many others

Application – Outcome Statistics

Service Desire

Category	N	Percent
Unknown	17153	48.1
Want to let leave	8817	24.7
Want to keep	5050	14.2
Beyond control	4637	13.0

Service Member's Desire

Category	N	Percent
Unknown	7445	20.9
Want to leave	20934	58.7
Want to stay	7117	20.0
Beyond control	161	0.5

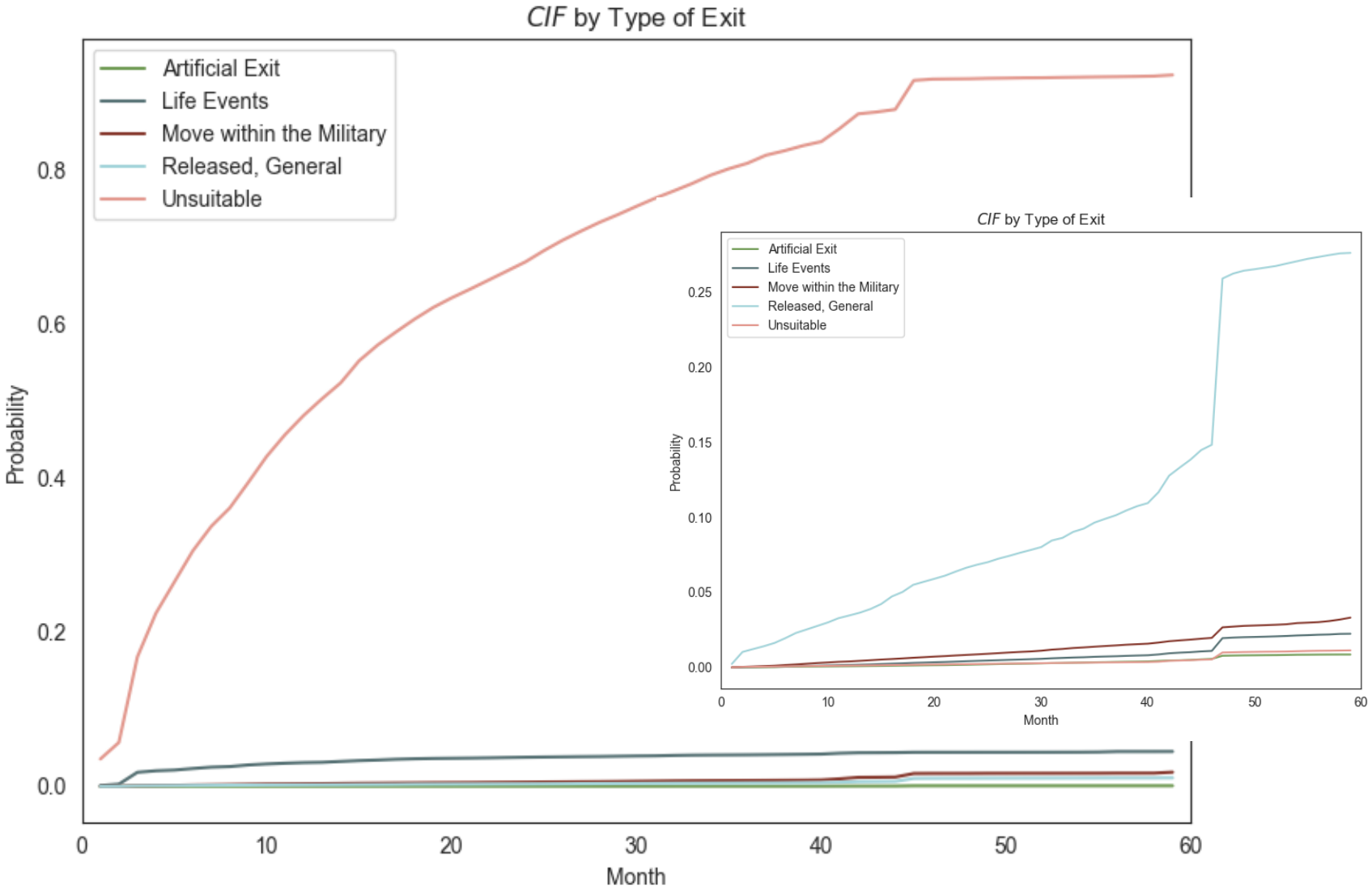
Service Member's Choice

Category	N	Percent
Voluntary	21580	60.5
Involuntary	12058	33.8
Unknown	2019	5.7

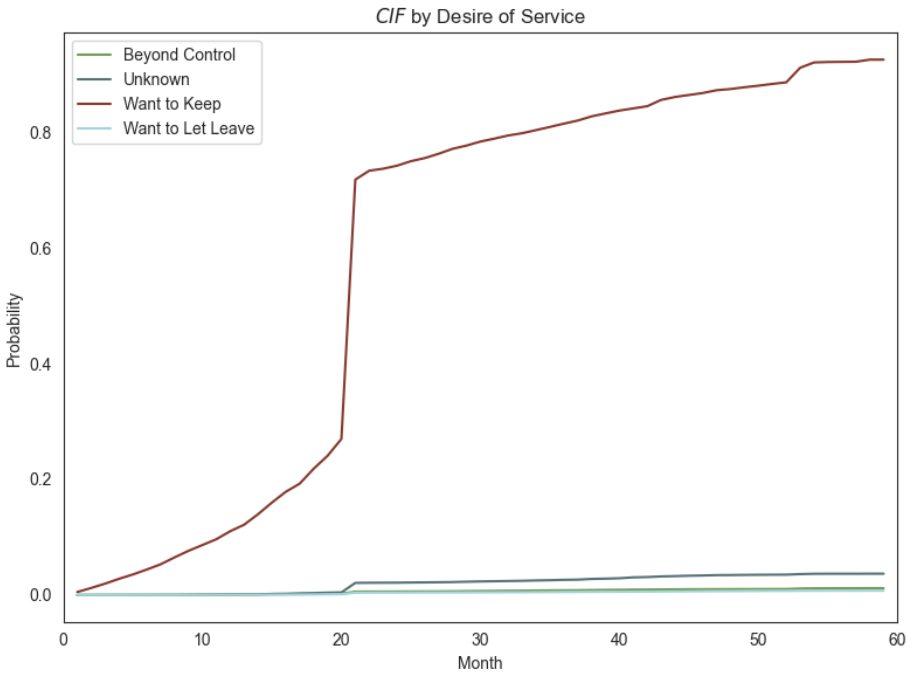
Exit Group

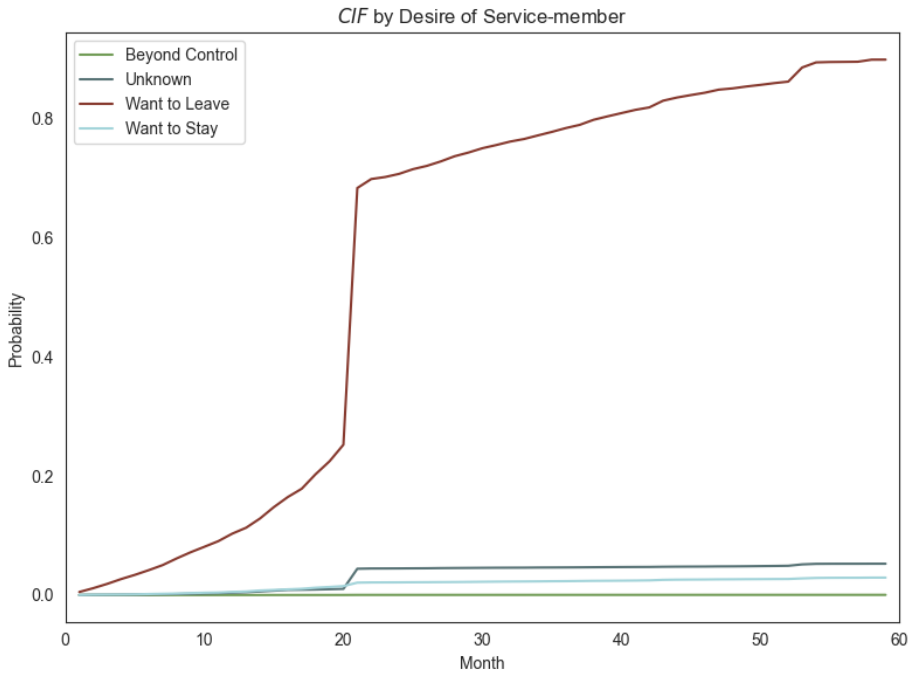
Category	N	Percent
Artificial Exit	638	1.8
Released, general	6180	17.3
Life Events	4700	13.2
Unsuitable	7177	20.1
Move within military	16962	47.6

Application – Forecasting Exit into "Unsuitable"



Application – Forecasting Want to Keep/Want to Leave





Conclusion

We started with the ability to forecast survival of individual service members

We expanded this capability to forecast exit into multiple states

The competing risks framework allows us to forecast both timing and manner of exit of individual service members

Performance looks good so far

We demonstrated its use in flagging service members for interventions

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Appendix

Appendix: Summary Statistics

How the 36,280 USN personnel attrited in FY 2019

Character of service	Number (total)	%	Number (enlisted)	%	Number (officer)	%
Honorable	24,625	68%	20,983	65%	3,642	90%
Uncharacterized	7,535	21%	7,535	23%	0	0%
Under honorable conditions	1,882	5%	1,821	6%	61	2%
Missing	1,241	3%	907	3%	334	8%
Under other than honorable conditions	941	3%	924	3%	17	<1%
Bad conduct	56	<1%	56	<1%	0	0%
Total	36,280		32,226		4,054	

Reenlistment eligibility of FY 2019 enlisted attritions

Eligibility criteria	Number	Percent
Eligible	13,563	42%
Eligible with waiver	5,614	17%
Ineligible	4,487	14%
Eligible with restrictions	3,884	12%
Temporary medical condition or unsatisfactory initial performance	3,329	10%
Missing	1,117	3%
Ineligible due to high tenure	232	1%
Total	32,226	

Top 10 reasons of separation for officers and enlisted

Reason (officer)	Number	%*
Expiration of term of service	1,284	33%
Retirement, 20 – 30 years	1,113	28%
Retirement, failure of selection for promotion	388	10%
Unknown	312	8%
Retirement, 30+ years	308	8%
Failure of selection for promotion	201	5%
Involuntary release	103	3%
Retirement, other	73	2%
Temporary disability	71	2%
Unfitness or unacceptable conduct	54	1%
Total	3,907	

Reason (enlisted)	Number	%*
Expiration of term of service	13,452	46%
Retirement, 20 – 30 years	3,581	12%
Erroneous enlistment or induction	3,385	12%
Unqualified for active duty	2,229	8%
Entry level performance and conduct	1,867	6%
Drugs	1,119	4%
Fraudulent entry	983	3%
Unknown	976	3%
Temporary disability retirement	964	3%
Commission of serious offense	869	3%
Total	29,425	

*Percentage out of top 10 reasons, not total separations

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14. ABSTRACT

Accurate, high-fidelity predictions of complex events can provide important information in many research, managerial, and operational contexts. Our open-source software package, the Finite-Interval Forecasting Engine (FIFE) provides a flexible, machine learning toolkit for forecasting panel attrition. Constructed to facilitate reuse and adaptation, FIFE is not bound to a single use case: it can accommodate any process wherein a subject—such as a person, group, or equipment item—is observed over multiple periods before potentially transitioning to one or more exit states. The algorithms within FIFE build on and generalize traditional tools for survival analysis in a machine learning context. FIFE can be used for both binary and competing risk survival analysis. FIFE also includes a suite of built-in tools for data preprocessing, metrics, hyper parameter optimization, and visualizations.

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