BREAKING THE LOOP

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BACKGROUND

- In local jails in the US, 64% of people struggle with mental illness, 68% have a substance abuse disorder, and 44% suffer from chronic health issues. (Source: 2006 Bureau of Justice Statistics Special Report, James and Glaze)
- Can lead to recidivism and **high social and economic costs**: vicious cycle
- In addition, a large proportion of such cases are related to **low-scale, non-violent crimes**.
- Low effectiveness of uncoordinated rehabilitation efforts.
- If, instead, people with mental illness received the services they needed in time, we could potentially prevent the situations where they would get arrested, go to jail, and/ or face charges in court.
- Due to local budget constraints, only **a very limited number of people** can be intervened with targeted health treatment by local authorities, every year.

EARLY INTERVENTION

How this problem has been tackled so far?

- In general, intervened individuals are selected by area-experts via **heuristics** (i.e. by intuitions/correlations/ rules of thumb based on their experience in the field)
- A few **data-oriented prototypes** have been developed at a local county level (e.g. Johnson County, KS and others, as part of the Obama White House's Data-Driven Justice Initiative).
  - These models have performed better than randomly assigned treatments and area-expert heuristics.

Our Proposed Approach

- Local authorities traditionally select the 200 highest-risk individuals through heuristics: we believe that more sophisticated and effective approaches are possible via tailored machine learning algorithms.
- Further, we investigate if exploiting differentiation between age groups could potentially expand the scope of intervention.

GOALS

DEVELOP A RISK-ASSESSMENT MODEL TO **PROACTIVELY** INTERVENE THE MOST VULNERABLE INDIVIDUALS BY CONNECTING SOCIAL AND MENTAL HEALTH WORKERS WITH THEM TO **AVOID INCARCERATION**

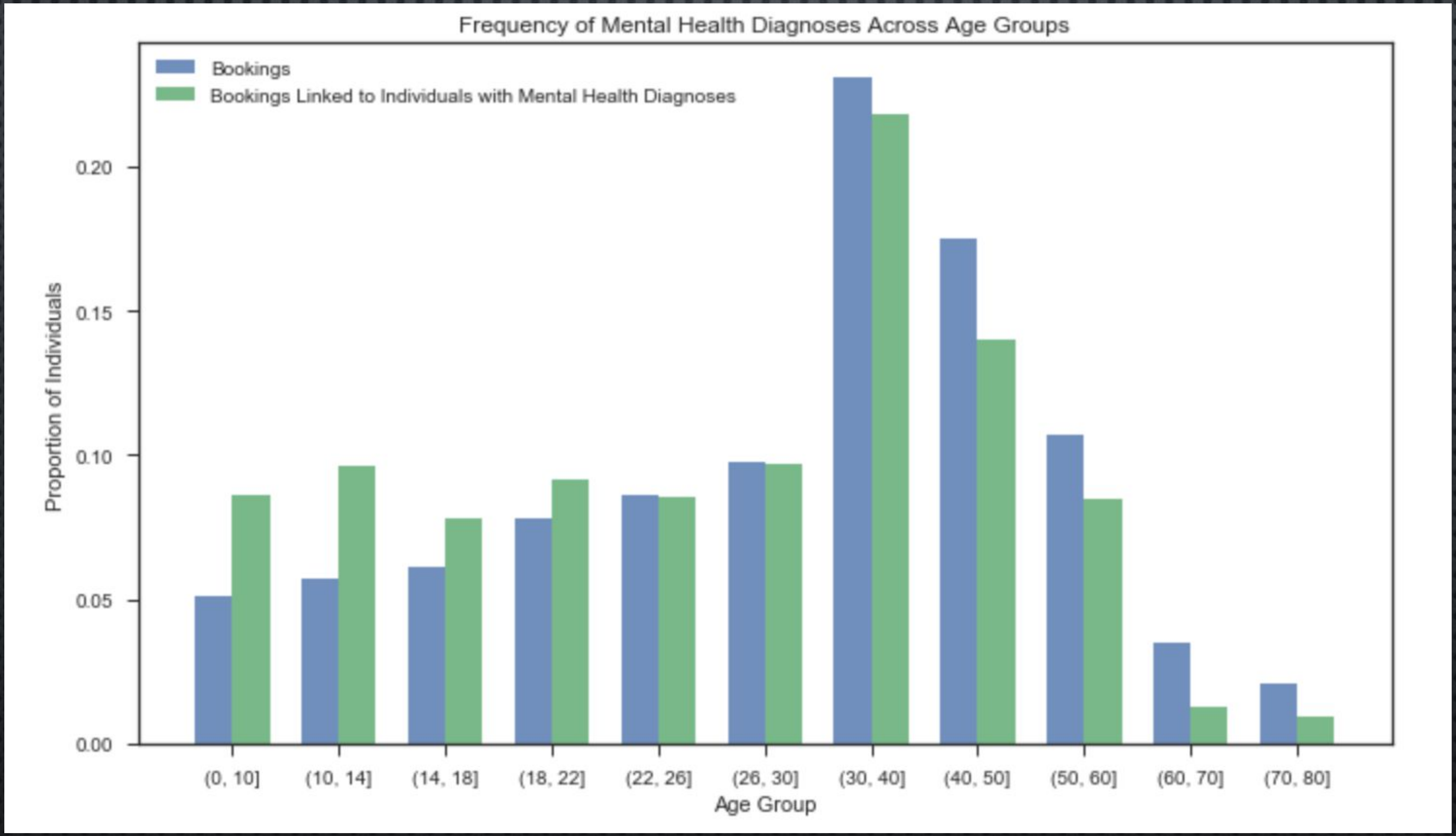
SPECIFIC QUESTION: GIVEN FEATURE VALUES XJ, HOW LIKELY IS IT THAT INDIVIDUAL J IS GOING TO RETURN TO PRISON WITHIN A YEAR?

ADDITIONAL GOAL: DIFFERENTIATE RISK ASSESSMENT AMONG AGE GROUPS (<=18 VS > 18), SO THAT THE SCOPE OF INTERVENTION IS BROADENED (E.G. COLLABORATION WITH PUBLIC SCHOOL AUTHORITIES FOR THE **YOUNGEST GROUPS** TO SUPPORT BEYOND THE 200 INTERVENTIONS BUDGETED BY JOHNSON COUNTY, KA.)

DATA

- **Data we have:** Jail bookings, mental health and EMS services from jan 2010 to april 2016, from johnson county, ka.
  - **Includes**: Inmate data, medical and mental health services data, court record data for a population of over 50,000 individuals, including age, demographic information, residence tract and block group, medical and mental health diagnoses, mental health treatments, counseling records, and arrest/ charge details
- **Data we need:** Census data, cost of interventions, and potentially others (ex: comparisons to private jails, if data can be sourced).
  - **Currently Exploring**:
    - National datasets from the Bureau of Justice Statistics

Mental Health Distribution



ANALYSIS

- **WHAT**: DETECT KEY FEATURES (DEMOGRAPHIC, SOCIOECONOMIC, MEDICAL, AND OTHERS) THAT COULD BE INDICATIVE OF ADDITIONAL ARRESTS, AT INDIVIDUAL LEVEL
  - MANIPULATING AND AUGMENTING THE DATA VIA FEATURE GENERATION, FILLING MISSING VALUES WITH K-NN
  - EX: HAVE BEGUN EXPLORING LENGTH OF STAY ACROSS AGE GROUPS, UNDIAGNOSED DAYS, ETC
- **HOW**: TRAINING VARIOUS CLASSIFICATION (INITIALLY BINARY, POTENTIALLY MULTI-CLASS) ALGORITHMS OVER DIFFERENT SUBSETS OF THE DATASET AND PARAMETER VALUES, AND CHOOSING THE BEST-PERFORMING MODEL
  - EVALUATING TO FIND MOST APPROPRIATE (OR HIGHEST PERFORMING) MODEL ACROSS DECISION TREES*, RANDOM FORESTS*, SVMS*, LOGISTIC REGRESSION, K-NEAREST-NEIGHBORS , OTHER ENSEMBLE METHODS INCLUDING BAGGING, BOOSTING
  - CLASSIFICATION: INMATE RISK SCORE FOR RECIDIVISM
    - SECONDARY: INMATE ELIGIBILITY FOR ALTERNATE INTERVENTION RESOURCES (E.G., THROUGH SCHOOL SYSTEM FOR JUVENILES)

EVALUATION METRIC

- **Our target variable is overwhelmingly zero**: most samples in our data set do return to prison → "accuracy" is not indicative of performance (not balanced)
- **Instead, we are particularly interested in our algorithm performing well in terms of true positive detection (TP)**, and but at the same time, we care about it performing poorly in terms of throwing false negatives (FN), because of resource(budget) constraints.
  - **Our primary validation metrics will therefore be based on both Precision (TP / TP + FP) and Recall (TP / TP + FN).**
    - Ideally, our algorithm will strike a good balance between the two (there is a natural trade-off): For example: an appropriately weighted **F1 score.**

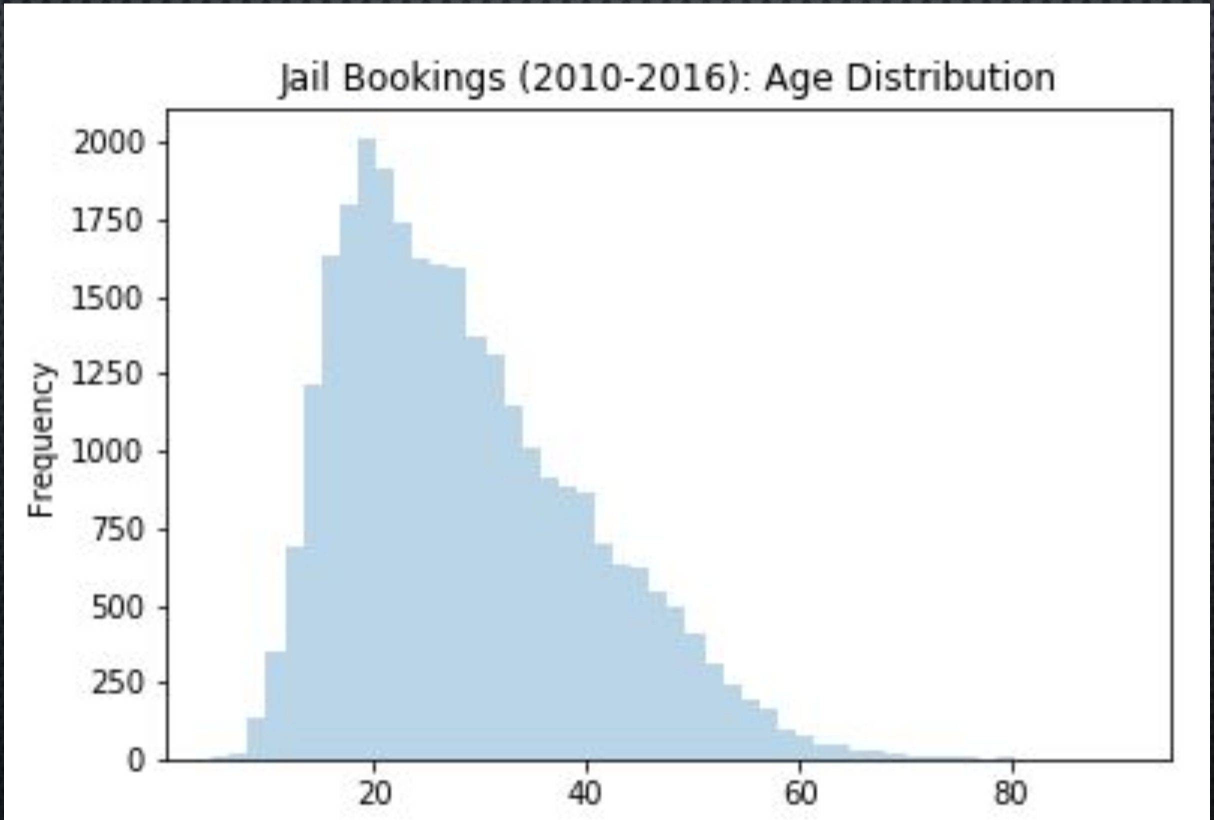
CAVEATS / LIMITATIONS

- **We do not have a "full picture" of samples due to unobservables**: e.g., parental income bracket, which could have bearing on outcomes of juvenile offenders after release
- **Only public service data are included in our dataset**: e.g., no private mental health data is available for comparison
- **Crucially, contacts with local law enforcement that do not result in a jail booking are not in the data**: (constrains the analysis)

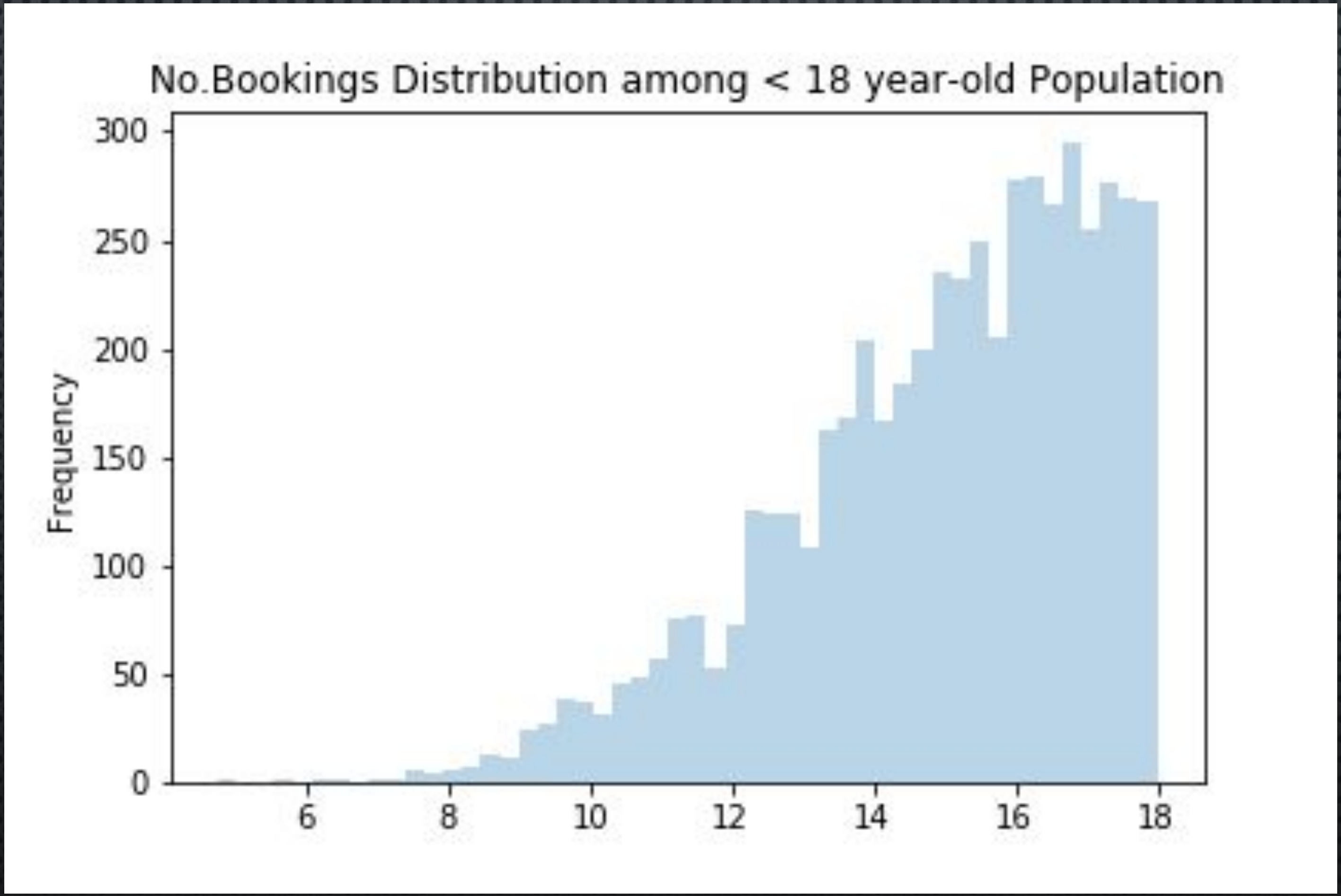
APPENDIX

APPENDIX: INITIAL EXPLORATION

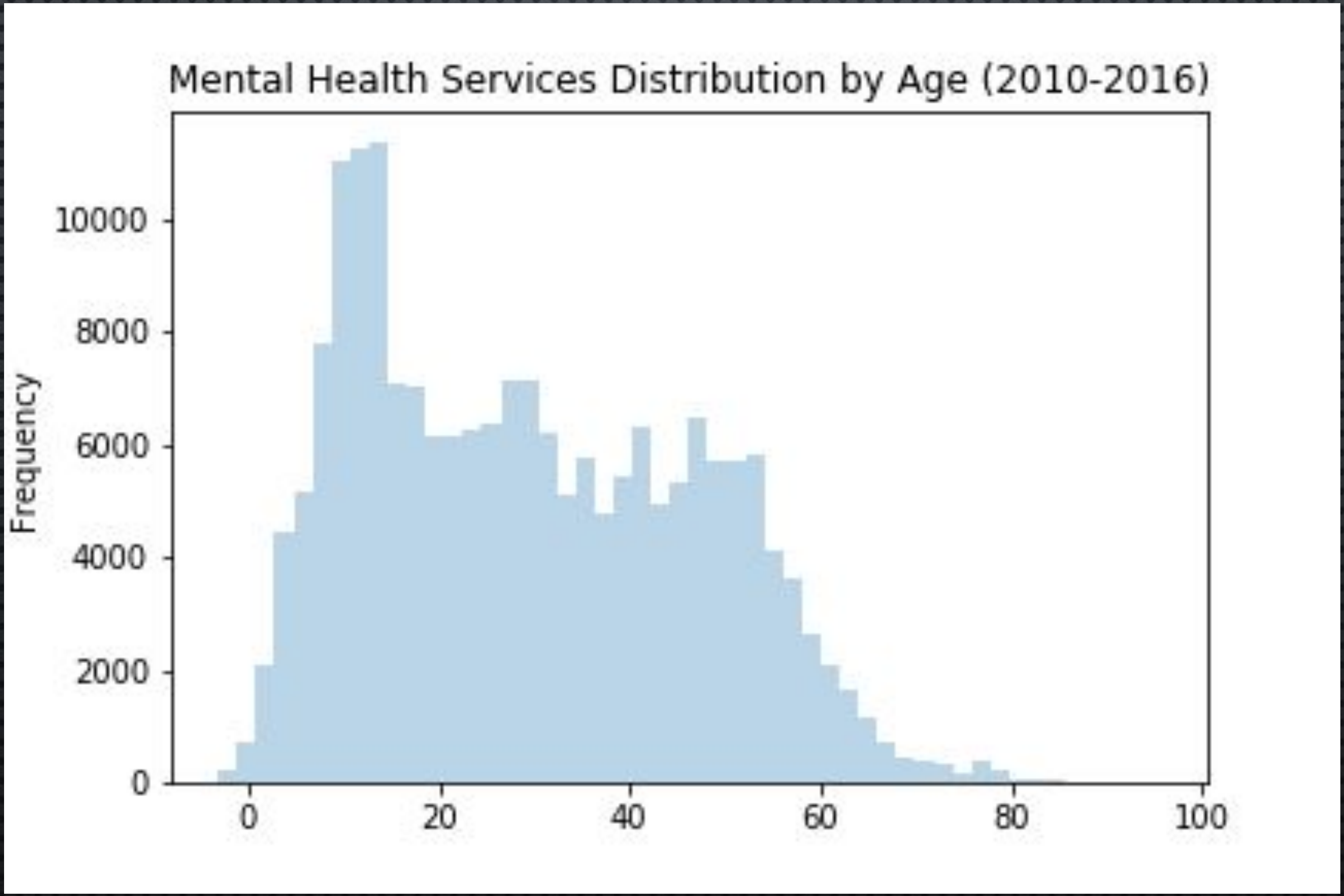
- After an **initial exploration** of the three main datasets we will use (jail bookings, EMS entries, and mental health entries) and eventually combine, we found several interesting stylized facts.
- However, a factor that we found particularly striking: differences among age groups, particularly between adults and non-adults



Bookings Distribution



Mental Health Services Distribution



Average length of prison stay by age group and race

	stay_days					
race	AMERICAN INDIAN OR ALASKA NATIVE	ASIAN	BLACK OR AFRICAN AMERICAN	NATIVE HAWAIIAN OR OTHER PACIFIC ISLANDER	OTHER RACE	WHITE
age_group						
(0, 10]			0.8			1.8
(10, 14]	2.4	5.3	55.5		5.9	11.1
(14, 18]	2.9	9.7	25.0		5.9	21.3
(18, 24]	13.6	21.5	29.5		36.1	19.6
(24, 30]	7.5	147.9	19.8	1	7.3	24.3
(30, 40]	10.2	15.3	16.3	1.3	5.3	28.0
(40, 50]	20.8	23.1	23.0	0	2	23.8
(50, 60]	132.2	11.4	26.0		21.5	15.4
(60, 70]	38.2	1.7	16.1		1.8	23.3
(70, 80]	6.2	0.9	19.0		1.7	39.2

Initial evaluation has given us places to start digging further: are these due to outliers, or systematic disparities?

Bail Amounts and Length of Stay in Jail by Age Group

	bail_amt			
	amin	mean	median	amax
age_cat				
(4.667, 13.336]	500.0	5675.4	2500.0	100000.0
(30.502, 39.086]	0.0	5405.4	2500.0	500000.0
(73.419, 82.002]	1000.0	5210.5	2500.0	25000.0
(21.919, 30.502]	0.0	5148.3	2500.0	250000.0
(47.669, 56.252]	0.0	5047.5	2500.0	300000.0
(39.086, 47.669]	0.0	4992.2	2500.0	250000.0
(56.252, 64.835]	0.0	4969.0	2500.0	100000.0
(13.336, 21.919]	0.0	4888.0	2500.0	500000.0
(64.835, 73.419]	250.0	4314.7	2500.0	100000.0
(82.002, 90.585]	0.0	2142.9	2500.0	3500.0

	len_stay			
	amin	mean	median	amax
age_cat				
(73.419, 82.002]	0.0	72.1	1.0	784.0
(47.669, 56.252]	0.0	31.8	1.0	725.0
(21.919, 30.502]	0.0	31.3	1.0	1390.0
(39.086, 47.669]	0.0	29.5	1.0	1173.0
(30.502, 39.086]	0.0	28.7	1.0	1318.0
(13.336, 21.919]	0.0	25.6	1.0	849.0
(56.252, 64.835]	0.0	20.3	1.0	652.0
(64.835, 73.419]	0.0	19.8	1.0	582.0
(4.667, 13.336]	0.0	16.9	4.0	504.0
(82.002, 90.585]	0.0	6.1	1.0	26.0