Madison Police Department

Data Driven Early Intervention System

Center for Data Science and Public Policy

THE UNIVERSITY OF CHICAGO

DSaPP Background

50+ partners

Public Safety
Public Health
Economic Development
Education
Environment
Infrastructure
Social Services


Roy Austin
Deputy Assistant to the President and Directo
of the Office of Urban Affairs, Justice and
Opportunity, Domestic Policy Council

DSaPP EIS Partner Departments

Policy Reasons for Implementing an EIS

An EIS helps:

- identify officers at high risk of having adverse incidents to facilitate individually tailored support (training, counseling, etc)
- identify officers at low risk of having adverse incidents to develop new support options
- meet (growing) national standards
- reduce liability
- build and maintain public trust
- set an example for other departments.

The Police Chief

Building Better Early Intervention Systems

Crystal Cody, Estella Patterson, and Kerr Putney, Charlotte-Mecklenburg, North Carolina, Police Department

Jennifer Helsby, Joe Walsh, Lauren Haynes, and Rayid Ghani, University of Chicago, Illinois

Samuel Carton, University of Michigan

Kenneth Joseph, Carnegie Mellon University, Pittsburgh

Ayesha Mahmud, Princeton University, New Jersey

Youngsoo Park, University of Arizona

Example Adverse Incidents

complaint from a citizen or colleague

Sustained

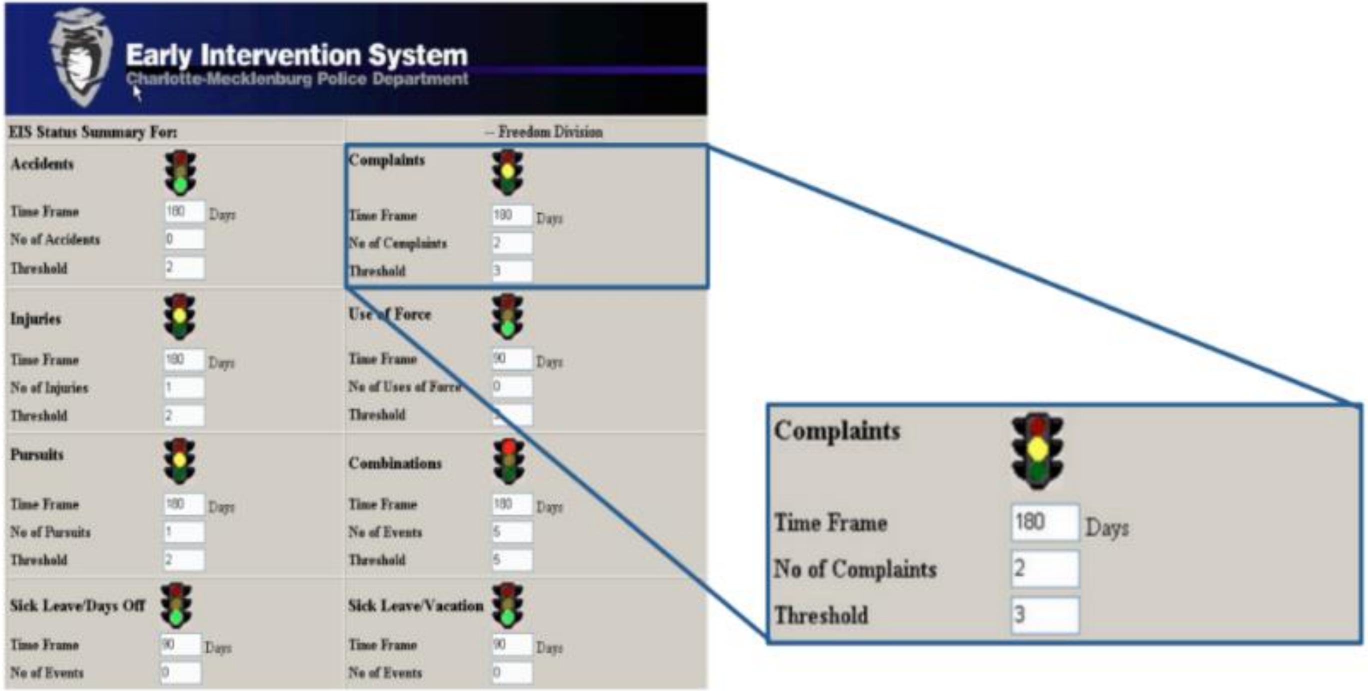
use of force or other tactics

Unjustified

accident or injury

Preventable

CMPD: Existing EIS



Concerns Raised by Departments

Other departments raised the following concerns about existing EIS:

- too simplistic: inaccurate, no context
- yes/no outcome: no ranking by risk
- potentially gameable
- does not adapt / improve
- no insights on supervision
- doesn’t learn from other departments

Early Intervention System
Charlotte-Mecklenburg Police Department

Welcome:

Display all current alerts for the employees you supervise

Display Risk Review Dashboard

Search Employee EIS History: [Last Name] [First Name] [Code #] [Search]

View Employee: [Select employee name V]

Create a Supervisor-Initiated alert for this Employee: [Create]

Create a Compliment: [Create]

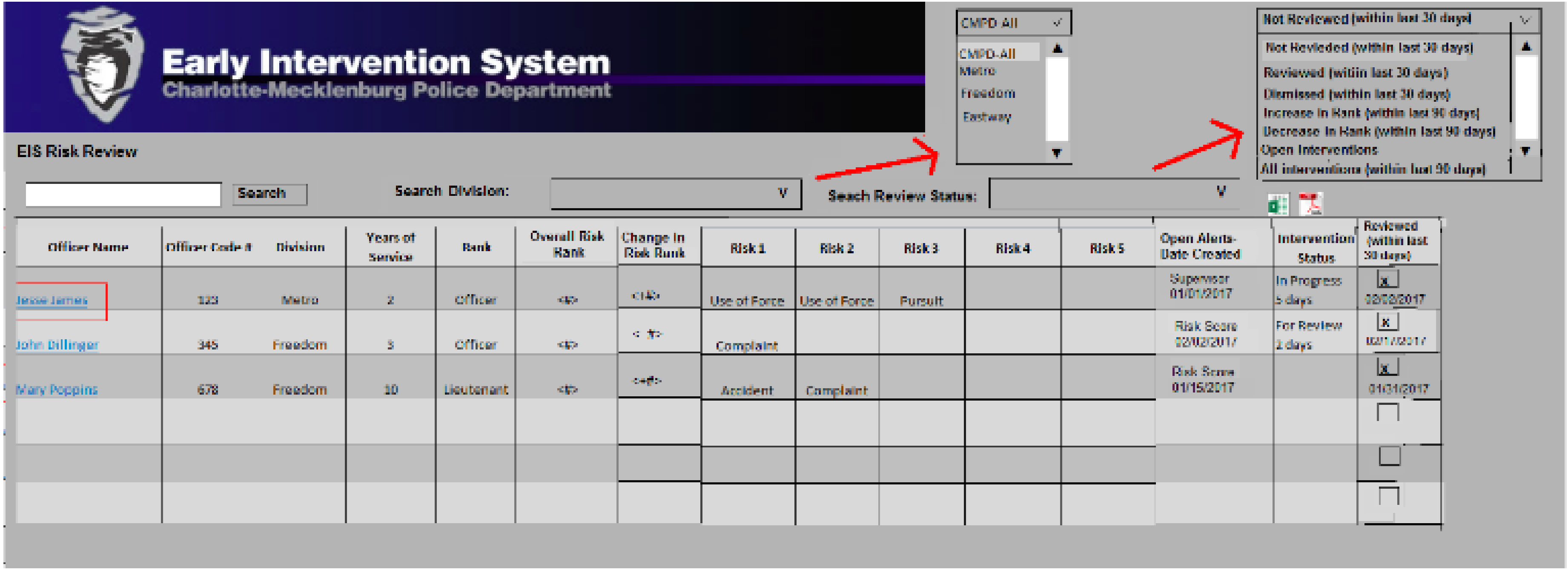
The following employees assigned to you have alerts:

EIS No	Name	Alert Type - Reason	Date Opened	Date Closed	# Days Open	Status	Assigned To	# Days Assigned	Action Taken
EI-11-1111	Smith, John L. (1234)---Police Reserves Unit	Supervisor Initiated - Sudden Performance Changes	4/15/2017		32	In Progress	Murray, Josh	32	
EI-13-0001	Albarth, Mike (4885)---Eastway Division	Risk Rank	1/15/2017	1/31/2017	16	Closed	Brackney, Donald	16	Training
EI-13-0021	Shaulis, Jackie (4567)---Hickory Grove Division	Risk Rank	1/20/2017	1/25/2017	5	Closed	Yoder, Brian	5	Counseling
EI-14-0115	Rome, Rodney D. (5566)---Metro Division	Supervisor Initiated - Complaints	3/24/2017		53	In Progress	Johnson, Shelly	52	No Intervention Required

Action Required:

EIS No	Name	Alert Type - Reason	Date Opened	Date Closed	# Days Open	Status	Assigned To	# Days Assigned	Action Taken
EI-11-1234	Doe, John (7890)---Westover Division	Supervisor Initiated Sudden Performance Changes	4/15/2017		32	In Progress	Murray, Josh	32	

CMPD: Updated EIS



Officer 1	High number of rule of conduct violations in last 15 years	Officer was suspended in last 15 years	High number of counseling interventions after special investigations	High number of sustained complaints in the last 15 years
Officer 2	High number of counseling interventions after special investigations	High number of rule of conduct violations in last 15 years	High number of prior adverse incidents in last 15 years	High number of special investigations correctives written in last 15 years
Officer 3	High number of complaints against officer in last 15 years	High number of rule of conduct violations in last 15 years	Officer was suspended in last 15 years	High number of counseling interventions after special investigations
Officer 4	Officer has dealt with high number of domestic violence incidents	High number of special investigations correctives written in last 15 years	Officer was suspended in last year	High number of accidents in last 1 year
Officer 5	Officer has dealt with high number of suicide incidents	High number of preventable accidents in last 1 year	Officer uses weapons often	Officer was suspended in last 15 years

EIS Performance for CMPD

Existing Threshold-Based EIS

CMPD
• 2 accidents in last 6 mos • 3 complaints in last 6 mos • 2 officer injuries in last 6 mos • 3 UOF in last 6 mos • 2 pursuits in last 6 mos • 5 combinations in last 6 mos

Data Included in the System

- Officer data
  - demographics
  - ranks
  - assignments
  - complaints
  - sick leave
  - overtime
  - vacation
  - vehicle pursuits
  - tort claims
  - use of force incidents
  - on duty collisions
  - civil suits
  - traffic stops
  - weapon discharges/shootings

EIS Performance for CMPD - How we evaluate the system

Comparison of Model Performance Between Existing Threshold-Based EIS and the Data-Driven EIS.
Time Period: April 2, 2014 to April 1, 2015.

EIS Performance for CMPD

Comparison of Model Performance Between Existing Threshold-Based EIS and the Data-Driven EIS.
Time Period: April 2, 2014 to April 1, 2015.

357 officers had an adverse incident in this time of 2,103 total officers

EIS Performance for CMPD - A menu of options

Comparison of Model Performance Between Existing Threshold-Based EIS and the Data-Driven EIS. Time Period: April 2, 2014 to April 1, 2015.			
	Threshold based EIS (flags **154 officers** for training/counseling)	Our Data-Driven Prototype (set to flag **154 officers** for training/counseling)	Our Data-Driven Prototype (set to flag **5% = 105 officers** for training)

We compare the **existing EIS** against **two settings** of our Data-Driven EISs.
The two settings correspond to different amounts of support that can be made available.

EIS Performance for CMPD

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The EISs provide lists of officers that could be in need of intervention.	154	154	105 (5% of officers)

EIS Performance for CMPD

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The EISs provide lists of officers that could be in need of intervention.	154	154	105 (5% of officers)
All other officers are deemed *not* at risk.	1,949	1,949	1,998 (95% of officers)

EIS Performance for CMPD

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	Threshold based EIS (flags **154 officers** for training/counseling)
The EISs provide lists of officers that could be in need of intervention.	34
	120
All other officers are deemed *not* at risk.	1,949

Out of the 154 identified officers, some **do have** an adverse incident in the next year...

… and some **do not**.

EIS Performance for CMPD

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Identified officers who **did** go on to have an adverse incident	34
Identified officers who **did not** go on to have an adverse incident	120
All other officers are deemed *not* at risk.	1,949

EIS Performance for CMPD

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Identified officers who **did** go on to have an adverse incident	34	60 (+76%)
Identified officers who **did not** go on to have an adverse incident	120	94 (-22%)
All other officers are deemed *not* at risk.	1,949	

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Identified officers who **did** go on to have an adverse incident	34	60 (+76%)	31 (-9%)
Identified officers who **did not** go on to have an adverse incident	120	94 (-22%)	74 (-38%)
All other officers are deemed *not* at risk.	1,949		

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All other officers are deemed *not* at risk.	1,626 323		

Out of the unidentified officers, most **do not** go on to have an adverse incident in the next year...

… but some **do**.

EIS Performance for CMPD

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Unidentified officers who **did not** go on to have an adverse incident	1,626		
Unidentified officers who **did** go on to have an adverse incident	323		

EIS Performance for CMPD

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Identified officers who **did not** go on to have an adverse incident	120	94 (-22%)	74 (-38%)
Unidentified officers who **did not** go on to have an adverse incident	1,626	1,652 (+2%)	
Unidentified officers who **did** go on to have an adverse incident	323	293 (-9%)	

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Unidentified officers who **did not** go on to have an adverse incident	1,626	1,652 (+2%)	1,672 (+3%)
Unidentified officers who **did** go on to have an adverse incident	323	293 (-9%)	326 (-1%)

Questions?

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Joe : jtwalsh@uchicago.edu

Extra Slides

Early Intervention Systems: Predicting Adverse Incidents in Practice

Partner: Charlotte-Mecklenburg Police Department

Center for Data Science and Public Policy

THE UNIVERSITY OF CHICAGO

Adverse incidents

An officer can be involved in three main types of potential adverse incident:

A use of force

An accident

A complaint

Each is reviewed by the chain of command and/or Internal Affairs who determine whether it should be considered adverse.

Adverse incidents

An officer can be involved in three main types of potential adverse incident:

A use of force

Unjustified

An accident

Preventable

A complaint

Sustained

Each is reviewed by the chain of command and/or Internal Affairs who determine whether it should be considered adverse.

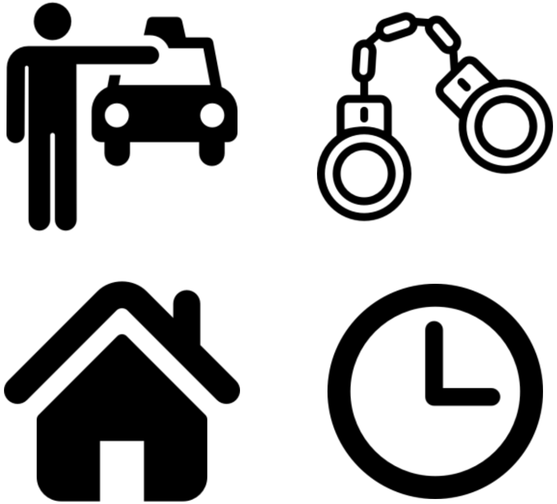
Officer level predictions

An officer...

Officer level predictions

An officer...

...has attributes and actions...

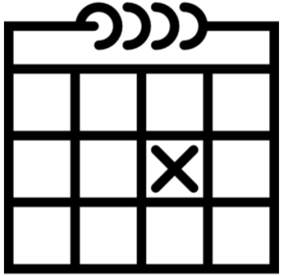


Officer level predictions

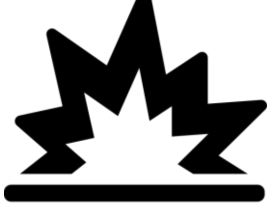
An officer...

...has attributes and actions...

...that may be predictive



...of adverse events.



The task:

Assess officers at risk of adverse incidents in a given time window.

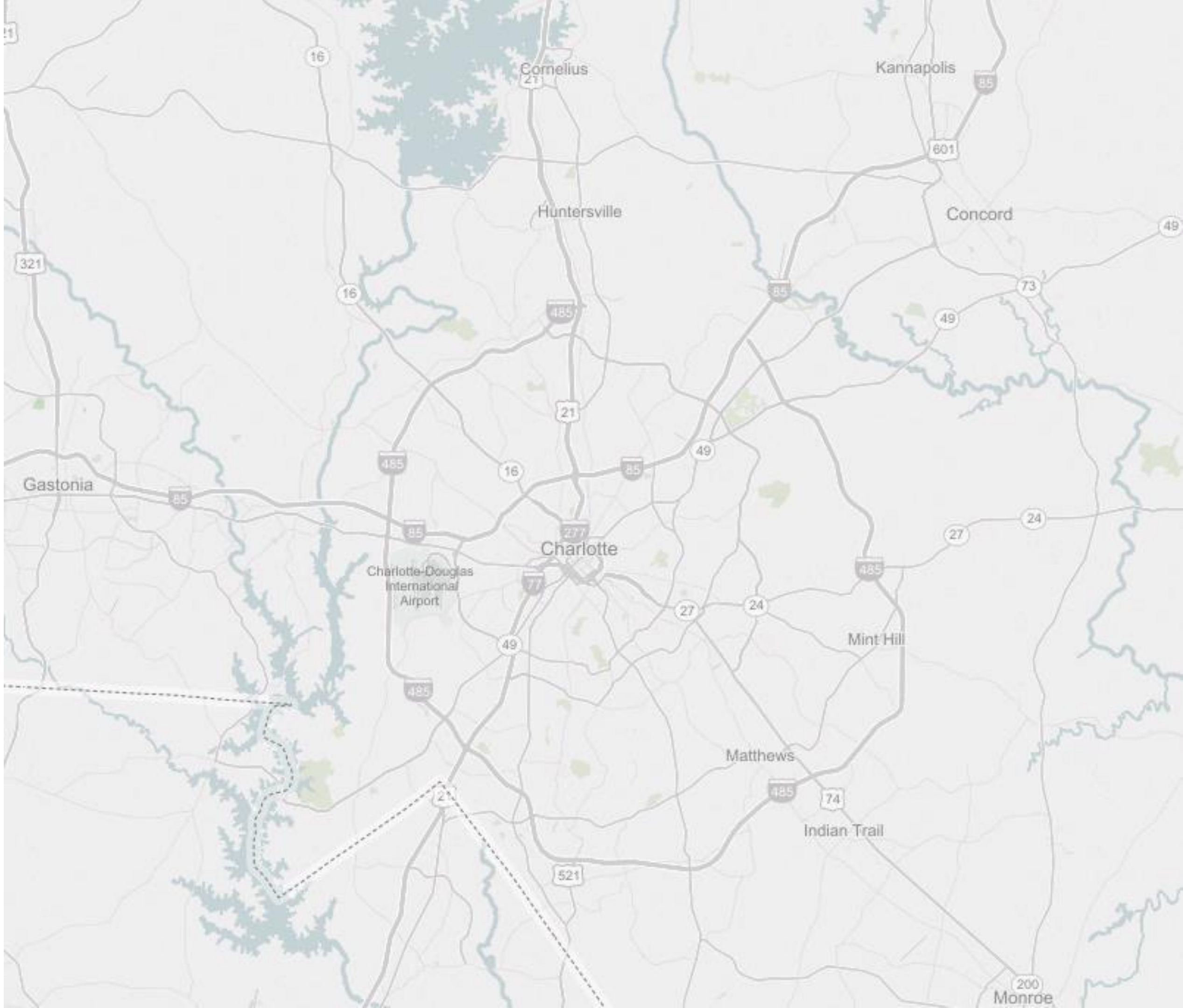
Washington
Montana
North Dakota
Minnesota
Oregon
Idaho
South Dakota
Wisconsin
Michigan
New York
Wyoming
Nebraska
Iowa
United States
Pennsylvania
Nevada
Utah
Colorado
Kansas
Illinois
Indiana
Ohio
West Virginia
Missouri
Kentucky
Virginia
California
Tennessee
North Carolina
Oklahoma
Arkansas
South Carolina
Arizona
New Mexico
Mississippi
Alabama
Georgia
Texas
Louisiana
Florida
Mexico

Charlotte, NC
The Queen City / The Hornets Nest
Founded: 1755

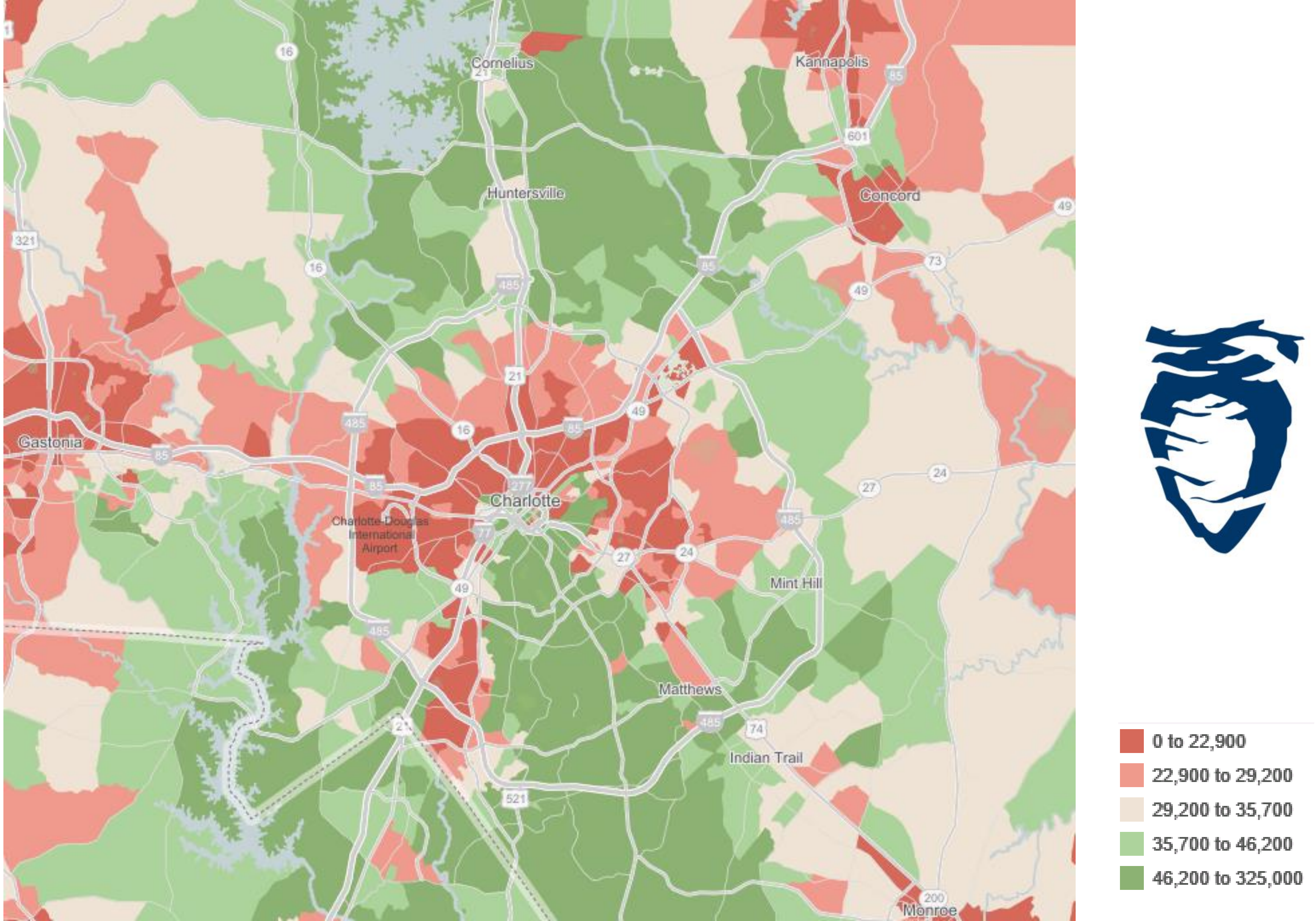
Area: 297 sq miles

Metro population 2014:
2.4 million

City population 2014:
809,000



Per capita income (2015)

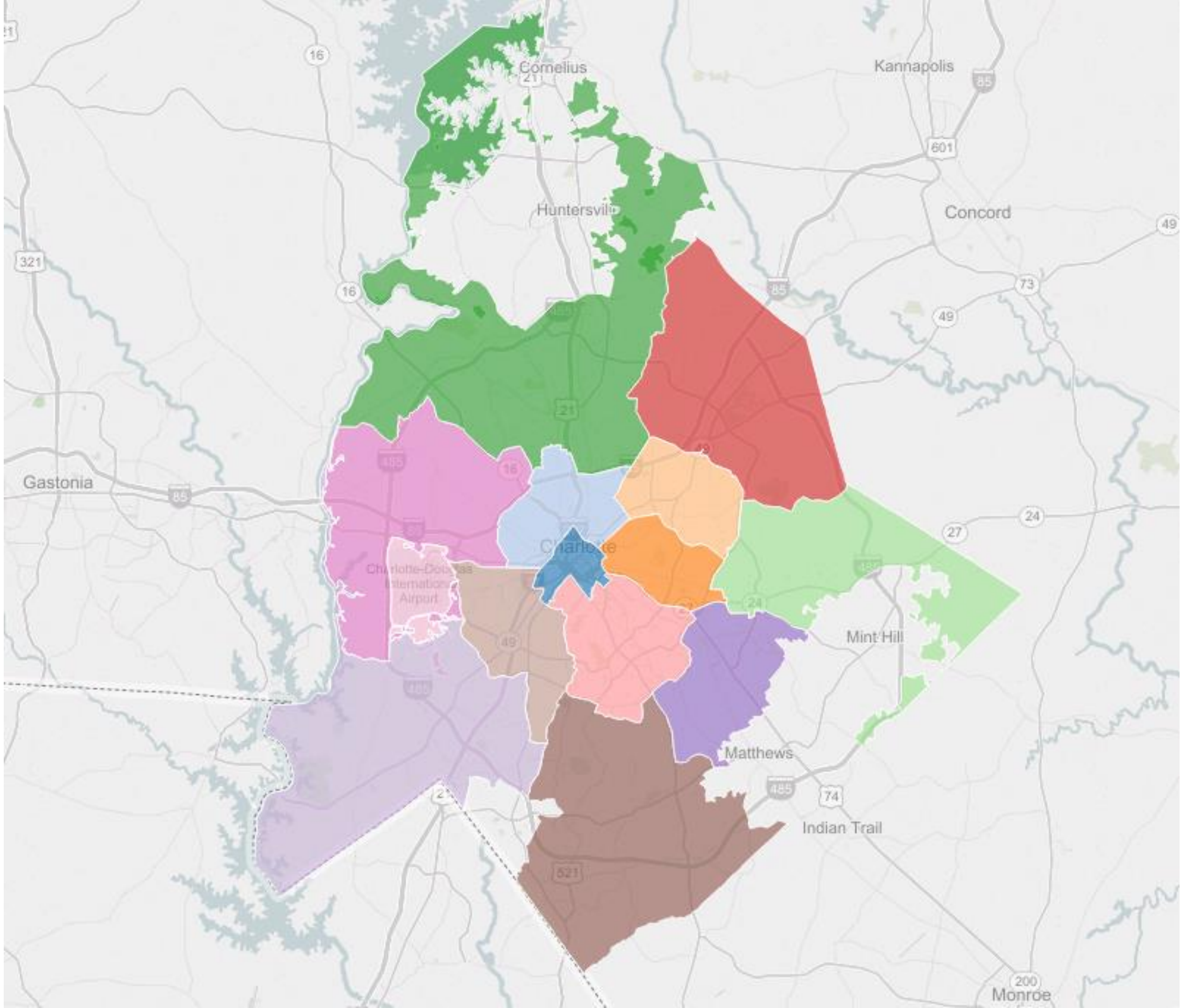


Charlotte - Mecklenburg Police Department

14 Divisions

~1800 sworn Officers

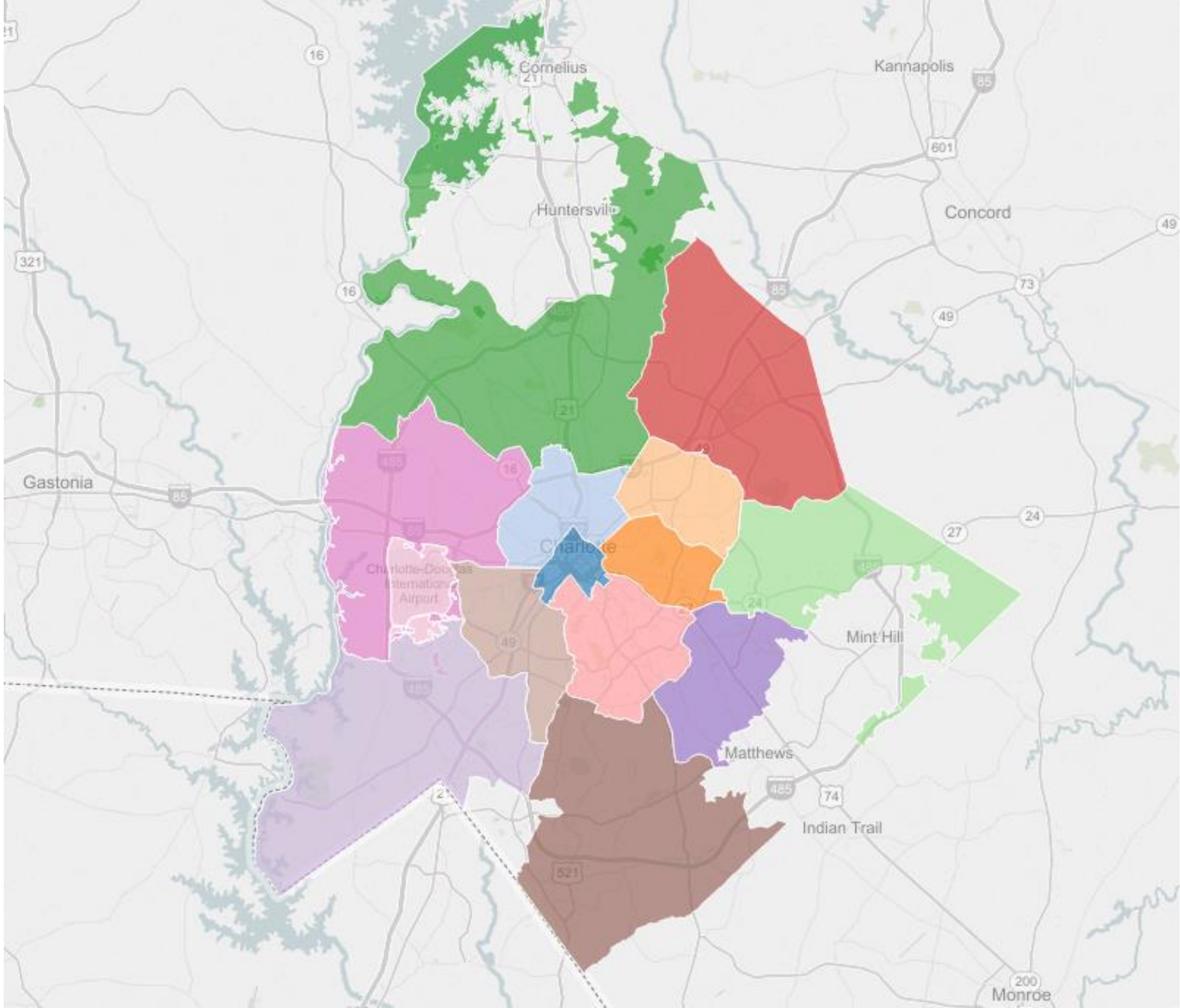
Crime rates steadily declining but still above average in US.



Time:
January 2005 - present

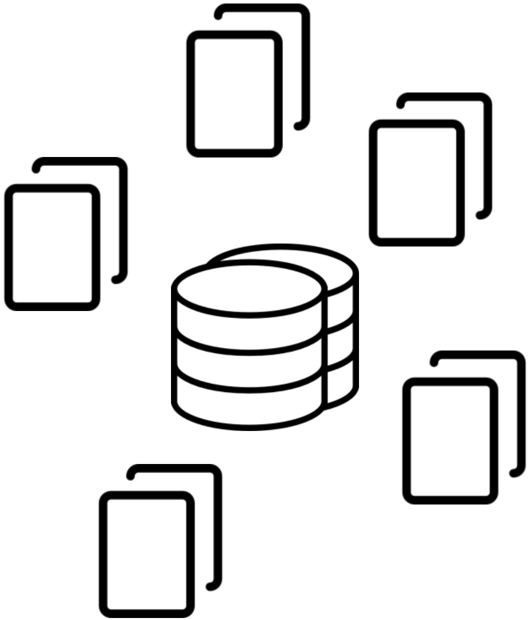
~12 million dispatches

Average of ~15,150 per week

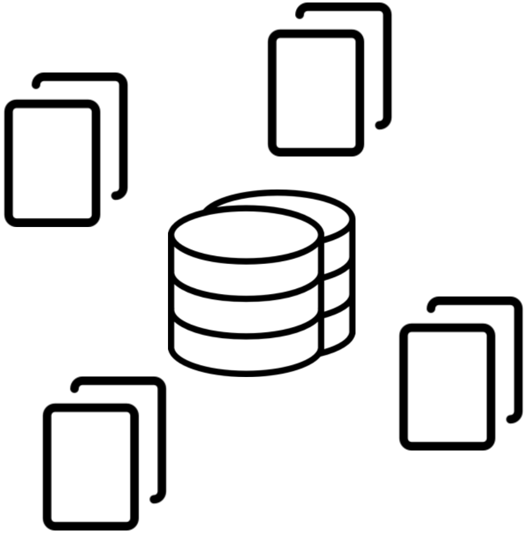


Different Department databases

Department A

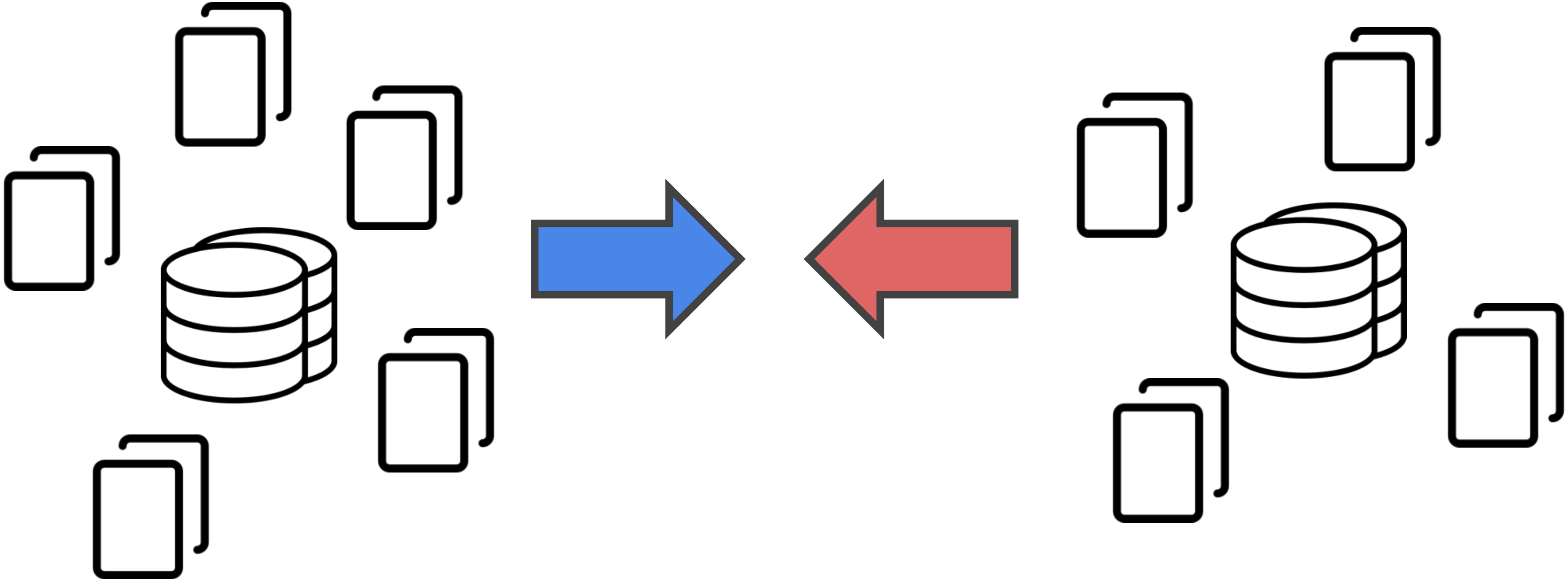


Department B



Different Department databases

Department A **Department B**

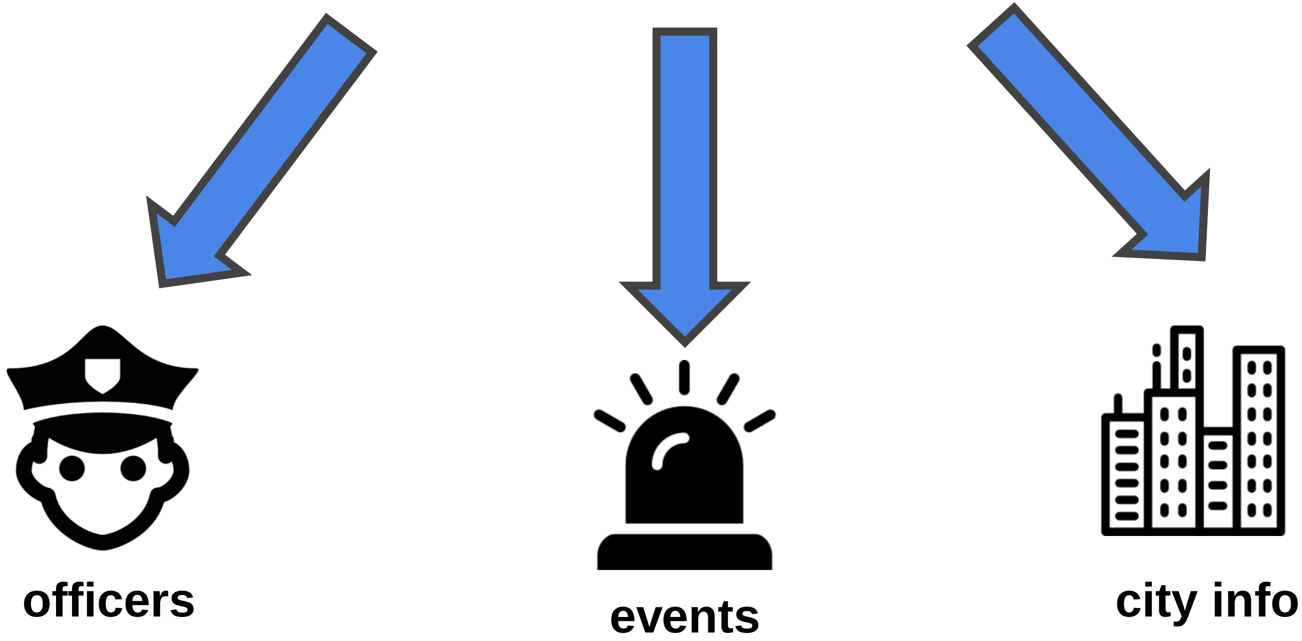


Different Department databases

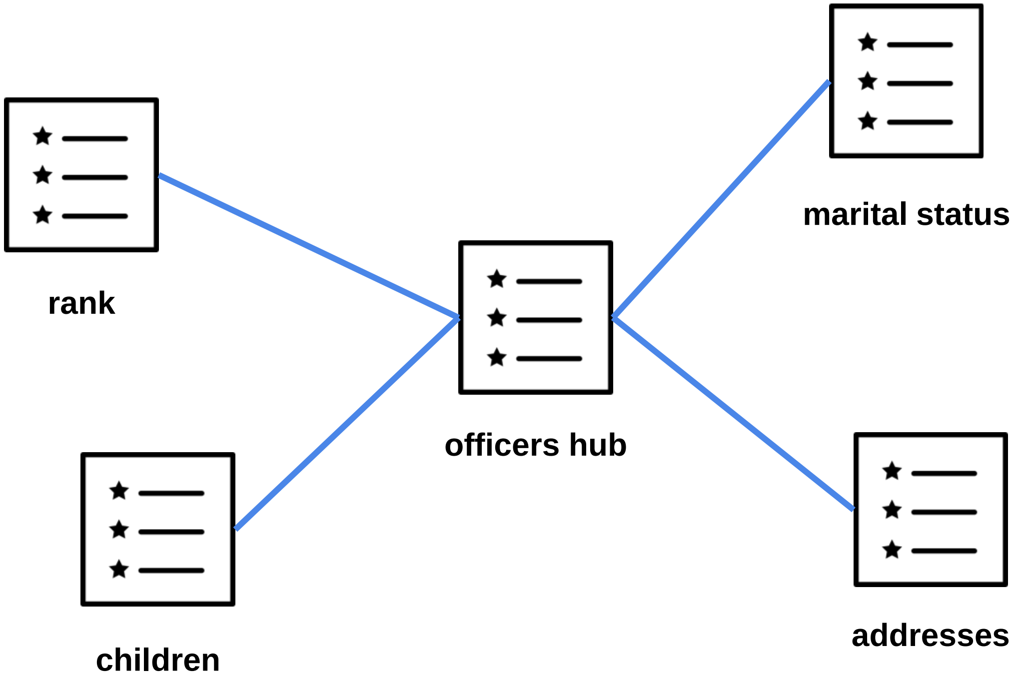
“Common police format”

aka staging tables

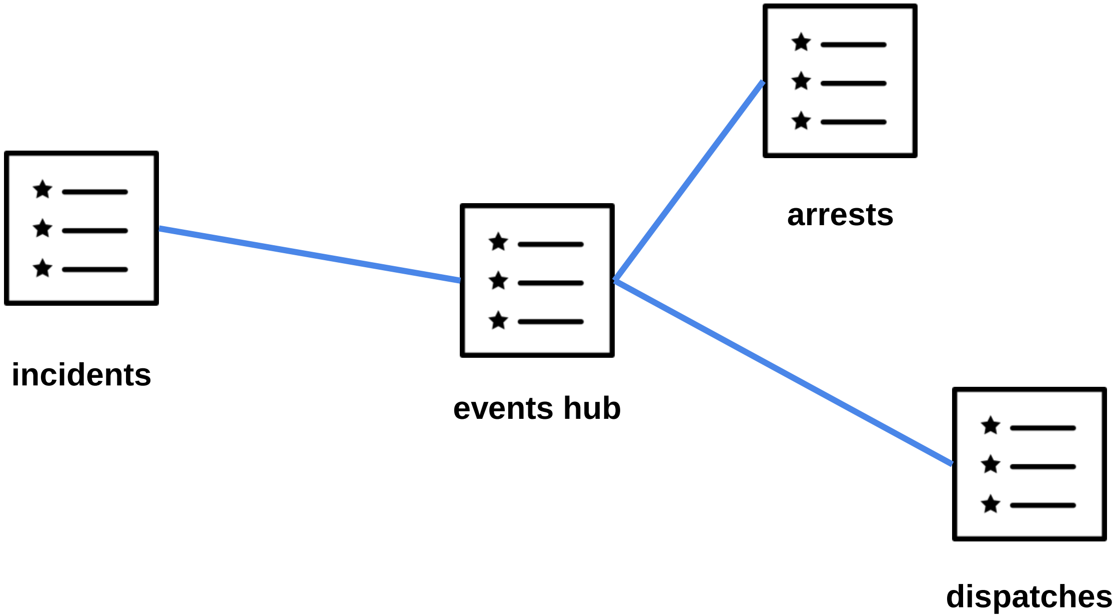
Common format has three conceptual parts:



Officers

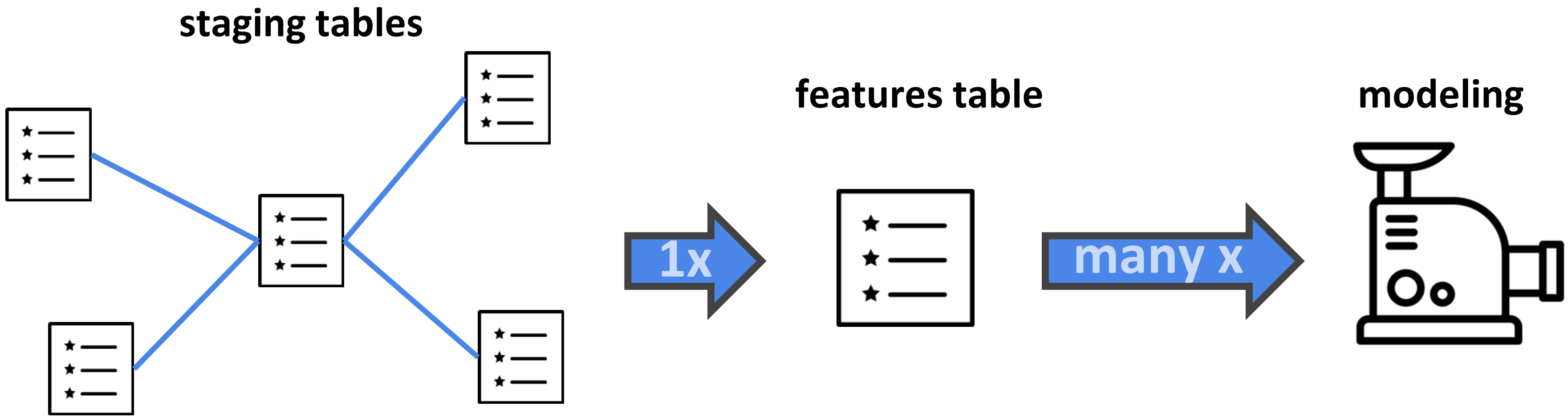


Events



Calculating features takes a while

… so we only want to do it once



Features

Groups (up to 3000 individual features)

- Incidents Reported
- Incidents Completed
- Officer Shifts
- Officer Arrests
- Traffic Stops
- Field Interviews
- Dispatches
- Officer Characteristics
- Demographic weighted Arrests
- Officer Employment
- Officer Compliments

Police Pipeline

Open source all the time: https://github.com/dssg/police-eis

Private police department specific repositories to map the raw data to the staging tables

So far: CMPD, MNPD and Pittsburgh

In progress: San Francisco

CMPD – Implementation Phase

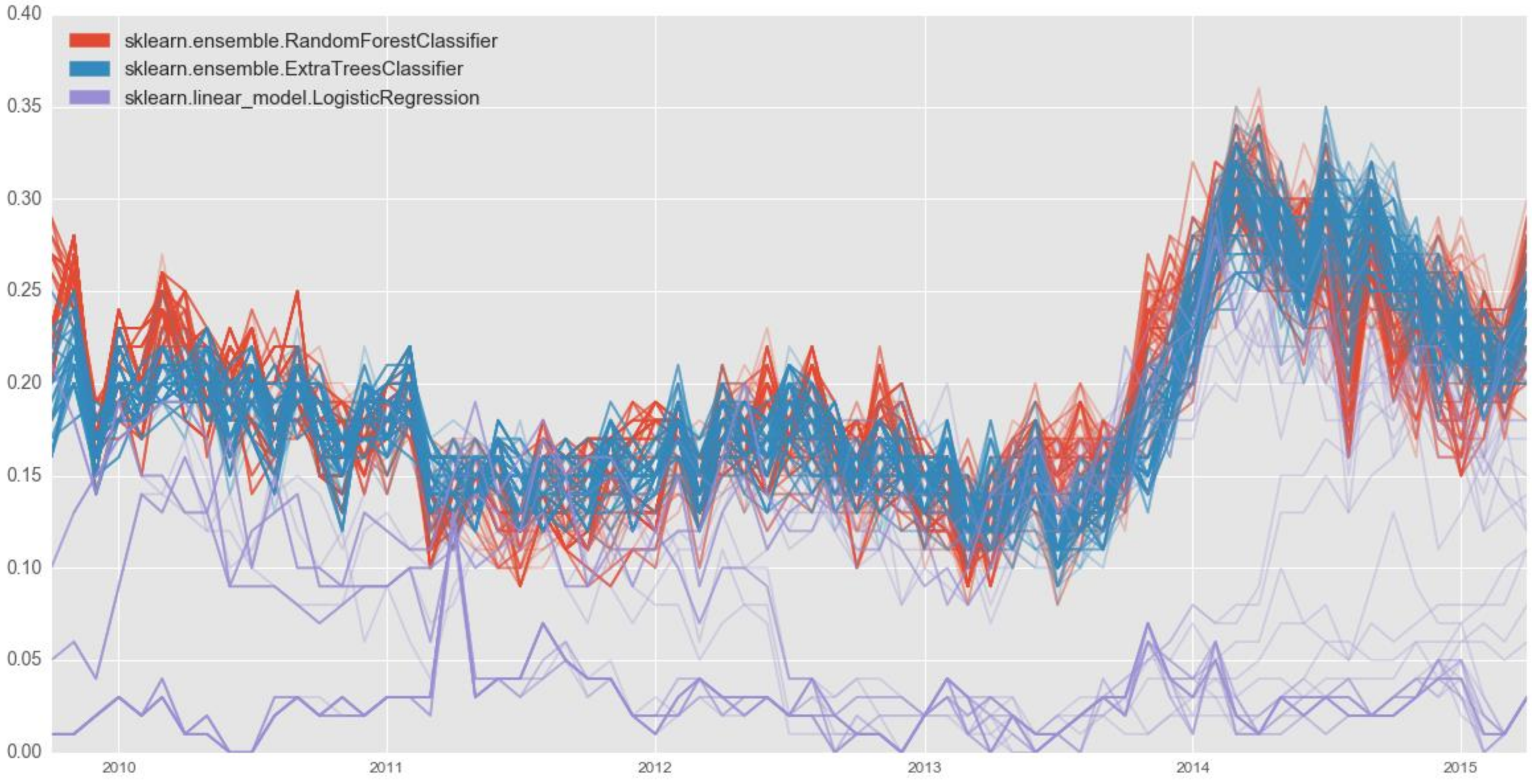
Daily predictions from 1st of August 2017

Professional Standards Captain will review the top 100 riskiest officers based on the Machine Learning assesment

For each selected officer, the raw data will be displayed to provide guidance

If an officer is indicated, the Sergeant of an officer is informed to decide on the intervention

Precision at top 100 over time



Input Data

Officer characteristics

Age

Gender

Marriage events

Academy records

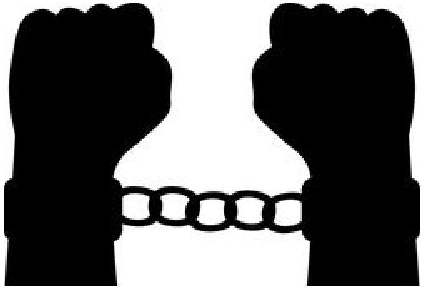
Incidents / internal affairs

Number of arrests

Counselling received

Number of allegations

Number of rule violations



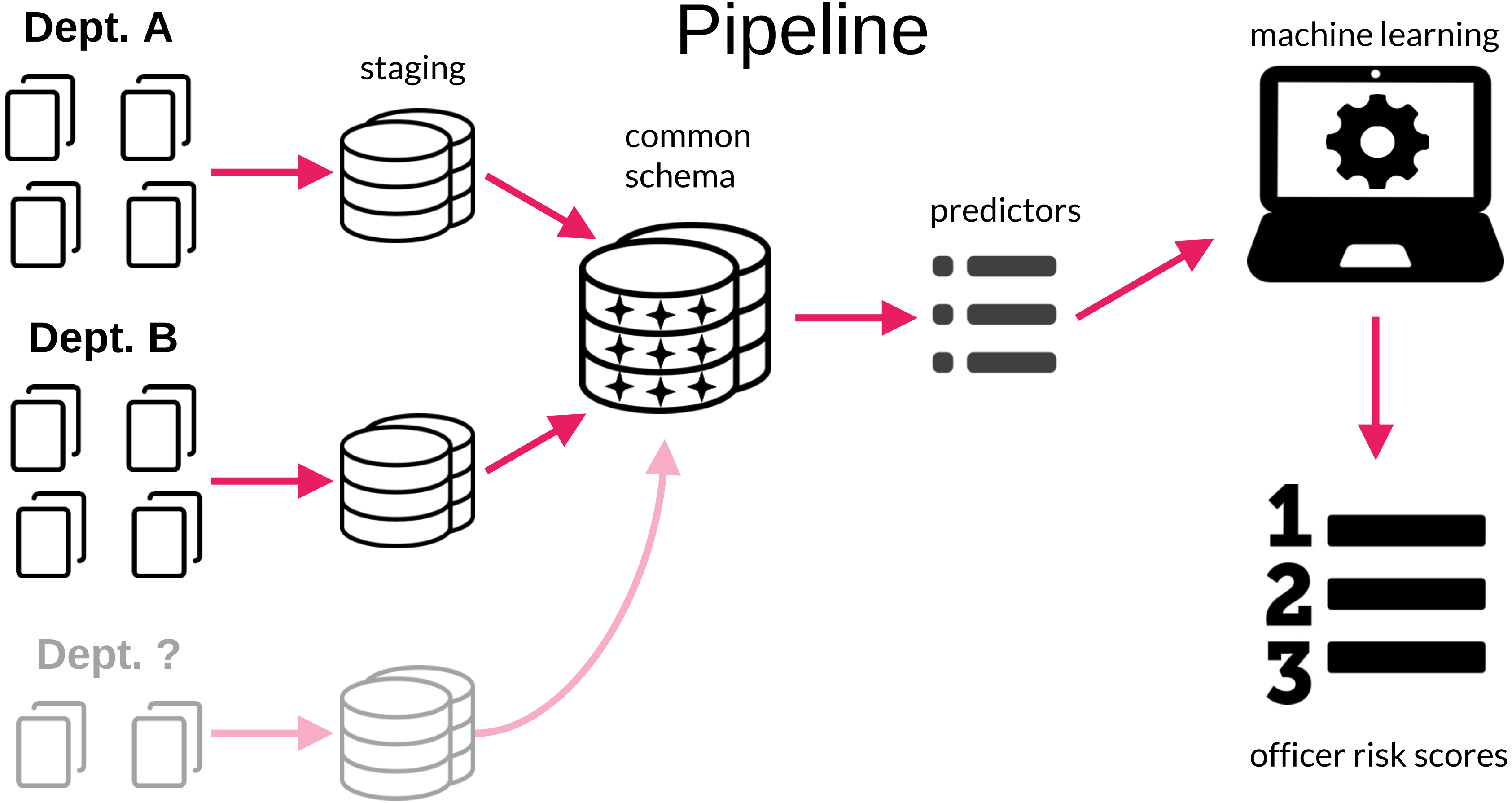
Shift level

Mean hours per shift

Shift type

Sick days taken

Pipeline


Dept. A
staging
common
schema
predictors
machine learning
Dept. B
Dept. ?
1
2
3
officer risk scores

Output

Officer ID	Risk Score	Risk Factor 1	Risk Factor 2	Risk Factor 3	Risk Factor 4	Risk Factor 5
1230834	0.4					
1329874	0.3					
1345366	0.67					
4326767	0.1					
2346573	0.07					
2345235	0.01					
2365375	0.02					