## Continued Improvements in Patient Deduplication:

Improving patient deduplication and overall data quality using artificial intelligence

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## Agenda

1. MIIS deduplication methods
2. Methodology and tools for analysis
3. High level goals of analysis
4. Comparing the 2018 data to 2017
5. Detailed review of individual match
 cases
6. Outcomes and updates

## Patient Deduplication System



## Massachusetts IIS Patient Deduplication

- The Massachusetts IIS (MIIS) currently uses a weight based algorithm that has been trained using both test data as well as production data.
- Prior to using an Al tool to evaluate the system we had to rely on users to report issues with deduplication.
- Last year we were able to evaluate and re-train the MIIS using Lantern (our Al tool).
- This was the largest retraining effort for our deduplication system since we began training with production data.


## Timeline of Patient Deduplication in the MIIS

## 06/2013 <br> MIIS v3.0

## 04/2014 MIIS v3.4.3

$\underline{\mathbf{2 0 1 3}}$ - The deduplication engine at this time had been trained only using test data.
2014 - The deduplication algorithm was re-trained with a large subset of production data.
2015 - The MIIS was updated to send a multiple birth indicator into the deduplication algorithm.

2017 - The Lantern tool was used to identify both code fixes and necessary re-training. Most notably training for sparsely populated records with null values in key fields.

## Concept for Lantern Person Matching Tool

- Develop a tool to do this analysis work automatically.
- The tool can sit outside of the IIS application, accessing the data via a DB connection.
- Configurable to be used with any record system.
- Lantern, would use deep learning technology (a form of AI) to learn patterns and accurately determine the probability that any two pairs are a match.
- Trained with Massachusetts production data.
- For any pair of records analyzed, a predicted matching probability would be produced.



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## Reducing the burden of Manual Matching

- In 2017 we had two goals for deduplication analysis:

1) Ensure that there are no incorrect auto merges occurring.
2) Reduce the size of the manual merge queue, the queue was too large for providers to effectively use.


## Probabilistic Analysis of Auto Merges

## Lantern Determined Probability of <br> Pairs that Auto Merged through 2017



## Probabilistic Analysis of Auto Merges

## Lantern Determined Probability of Pairs that Auto Merged after 2017 updates



## Probabilistic Analysis of Auto Merges

## Lantern Determined Probability of Pairs that Auto Merged after 2017 updates



## Auto Merge pairs with 50\% - 75\% Confidence

| Last Match | First Match | DOB Match | Middle Match | Address Match | Total Pairs | Pct Pairs |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| FALSE | FALSE | TRUE | TRUE | TRUE | 1 | 0.12\% |
|  | TRUE | FALSE |  | FALSE | 1 | 0.12\% |
|  |  | TRUE | FALSE | FALSE | 71 | 8.73\% |
|  |  |  |  | TRUE | 2 | 0.25\% |
|  |  |  | TRUE | FALSE | 2 | 0.25\% |
| TRUE | FALSE |  | FALSE | FALSE | 11 | 1.35\% |
|  |  |  |  | TRUE | 1 | 0.12\% |
|  | TRUE | FALSE |  | FALSE | 160 | 19.68\% |
|  |  |  |  | TRUE | 1 | 0.12\% |
|  |  |  | TRUE | FALSE | 29 | 3.57\% |
|  |  |  |  | TRUE | 1 | 0.12\% |
|  |  | TRUE | FALSE | FALSE | 533 | 65.56\% |
| Grand Total |  |  |  |  | $813$ |  |

## Auto Merge pairs with 50\% - 75\% Confidence

| Last Match | First Match | DOB Match | Middle Match | Address Match | Total Pairs | Pct Pairs |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| FALSE | FALSE | TRUE | TRUE | TRUE | 1 | 0.12\% |
|  | TRUE | FALSE |  | FALSE | 1 | 0.12\% |
|  |  | TRUE | FALSE | FALSE | 71 | 8.73\% |
|  |  |  |  | TRUE | 2 | 0.25\% |
|  |  |  | TRUE | FALSE | 2 | 0.25\% |
| TRUE | FALSE |  | FALSE | FALSE | 11 | 1.35\% |
|  |  |  |  | TRUE | 1 | 0.12\% |
|  | TRUE | FALSE |  | FALSE | 160 | 19.68\% |
|  |  |  |  | TRUE | 1 | $0.12 \%$ |
|  |  |  | TRUE | FALSE | 29 | 3.57\% |
|  |  |  |  | TRUE | 1 | 0.12\% |
|  |  | TRUE | FALSE | FALSE | 533 | 65.56\% |
| Grand Total |  |  |  |  | 813 |  |

## Example Patient Pair with $65 \%$ confidence

- Here is an example where Last, Middle, Address are not matching.
- We can see that we flagged the last name as not matching due to a space in one name. The Middle and Address do not match due to missing data, which we specifically trained for last year.

| Field | Patient A | Patient B |
| :--- | :--- | :--- |
| Last Name | De Jesus | DeJesus |
| Middle Name | Mark |  |
| First Name | Samuel | Samuel |
| Gender | Male | Male |
| Date of Birth | $01 / 01 / 2001$ | $01 / 01 / 2001$ |
| Street Address | 4 Oak Street |  |
| City | Boston |  |
| State | MA |  |

- Of this subset, where the last name, middle, and address did not match; a hyphen, space, or apostrophe in one of the last names accounted for $100 \%$ of the 71 merges that occurred.


## Auto Merge pairs with 50\% - 75\% Confidence

| Last Match | First Match | DOB Match | Middle Match | Address Match | Total Pairs | Pct Pairs |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| FALSE | FALSE | TRUE | TRUE | Pairs with last name that differ due to space, hyphen, or apostrophe. | 1 | 0.12\% |
|  | TRUE | FALSE |  |  | 1 | 0.12\% |
|  |  | TRUE | FALSE |  | +71 | $\frac{8.73 \%}{0.25 \%}$ |
|  |  |  | TRUE | FALSE | 2 | 0.25\% |
| TRUE | FALSE |  | FALSE | FALSE | 11 | 1.35\% |
|  |  |  |  | TRUE | 1 | 0.12\% |
|  | TRUE | FALSE |  | FALSE | 160 | 19.68\% |
|  |  |  |  | TRUE | 1 | $0.12 \%$ |
|  |  |  | TRUE | FALSE | 29 | 3.57\% |
|  |  |  |  | TRUE | 1 | 0.12\% |
|  |  | TRUE | FALSE | FALSE | 533 | 65.56\% |
| Grand Total |  |  |  |  | 813 |  |

## Example Patient Pair with $55 \%$ confidence

- Here is an example of First and Last Match and DOB, Middle, Address Not matching.
- We can see that training around swapped month and year was seen as just as confidant as matching DOB in the MIIS.

| Field | Patient A | Patient B |
| :--- | :--- | :--- |
| Last Name | Greenwood | Greenwood |
| Middle Name | M |  |
| First Name | Samuel | Samuel |
| Gender | Male | Male |
| Date of Birth | $08 / 07 / 2001$ | $07 / 08 / 2001$ |
| Street Address |  | 4 Oak Street |
| City |  | Boston |
| State |  | MA |

- These might be a better candidate for the manual merge queue, especially since we became less restrictive on matching middle and address we shouldn't be auto merging as much with swapped month and day.


## DOB Analysis Breakdown

- We evaluated the 160 pairs in this group that differ on DOB. - When EHR and IIS systems first launched there were many data quality issues, this required adjustments to compensate. Over time that data has become much cleaner.
- Here "fuzzy" logic designed to correct for typos in the DOB was pushing these pairs into the Auto Merge category.
$\square$



## Auto Merge pairs with 50\% - 75\% Confidence

| Last Match | First Match | DOB Match | Middle Match | Address Match | Total Pairs | Pct Pairs |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| FALSE | FALSE | TRUE | TRUE | Pairs with last name that differ due to space, hyphen, or apostrophe. | 1 | 0.12\% |
|  | TRUE | FALSE |  |  | 1 | 0.12\% |
|  |  | TRUE | FALSE |  |  | 8.73\% |
|  |  |  | TRUE | FALSE | 2 | 0.25\% |
| TRUE | FALSE |  | FALSE | FALSE | 11 | 1.35\% |
|  |  |  |  | TRUE | 1 | 0.12\% |
|  | TRUE | FALSE |  | Pairs used "fuzzy logic" to correct for DOB typos. May be good candidates for retraining. | $\frac{160}{1}$ | $\frac{19.68 \%}{0.12 \%}$ |
|  |  |  | TRUE | TRUE | 1 | 0.12\% |
|  |  | TRUE | FALSE | FALSE | 533 | 65.56\% |
| Grand Total |  |  |  |  | 813 |  |

## Probabilistic Analysis of Manual Merge Queue

Lantern Determined Probability of
60000
Pairs on the Manual Merge Queue (2017)


## Probabilistic Analysis of Manual Merge Queue



## Probabilistic Analysis of Manual Merge Queue



## Pairs on the Manual Queue with <60\% Confidence

| Last Match | First Match | DOB Match | Middle Match | Total Pairs | Pct of Pairs |
| :---: | :---: | :---: | :---: | :---: | :---: |
| FALSE | FALSE | FALSE | FALSE | 20 | 4.80\% |
|  |  |  | TRUE | 8 | 1.92\% |
|  |  | TRUE | FALSE | 80 | 19.18\% |
|  |  |  | TRUE | 11 | 2.64\% |
|  | TRUE | FALSE | FALSE | 49 | 11.75\% |
|  |  |  | TRUE | 12 | 2.88\% |
|  |  | TRUE | FALSE | 180 | 43.17\% |
|  |  |  | TRUE | 3 | 0.72\% |
| TRUE | FALSE | FALSE | FALSE | 5 | 1.20\% |
|  |  |  | TRUE | 1 | 0.24\% |
|  |  | TRUE | FALSE | 43 | 10.31\% |
|  | TRUE | FALSE | FALSE | 5 | 1.20\% |
| Grand Total |  |  |  | 417 |  |

## Pairs on the Manual Queue with <60\% Confidence

| Last Match | First Match | DOB Match | Middle Ma | Total Daine | Dct of Pairs |
| :---: | :---: | :---: | :---: | :---: | :---: |
| FALSE | FALSE | FALSE | FALSE | 20 | 4.80\% |
|  |  |  | TRUE | 8 | 93 |
|  |  | TRUE | FALSE | 80 | 19.18\% |
|  |  |  | TRUE | 11 | 2.64\% |
|  | TRUE | FALSE | FALSE | 49 | 11.75\% |
|  |  |  | TRUE | 12 | 2.88\% |
|  |  | TRUE | FALSE | 180 | 43.17\% |
|  |  |  | TRUE | 3 | 0.72\% |
| TRUE | FALSE | FALSE | FALSE | 5 | 1.20\% |
|  |  |  | TRUE | 1 | 0.24\% |
|  |  | TRUE | FALSE | 43 | 10.31\% |
|  | TRUE | FALSE | FALSE | 5 | 1.20\% |
| Grand Total |  |  |  | 417 |  |

## Example Patient Pair on Manual Queue with low confidence

- This is an example of one of the lowest confidence pairs on the queue, at just $14 \%$ confidence from Lantern.
- We can see enough similarities to understand why the system picked these records, but we may not want to allow users the opportunity to merge examples like this.
- This follows a similar pattern with the DOB still ranking at high confidence. If we do retraining for those DOB issues from the auto merge, the confidence level on this patient would drop too.

| Field | Patient A | Patient B |
| :--- | :--- | :--- |
| Last Name | Sample-One | Sample-Two |
| Middle Name | M |  |
| First Name | Julien | Jariel |
| Gender | Male | Male |
| Date of Birth | $10 / 02 / 2001$ | $02 / 10 / 2001$ |
| Street Address |  | 2 Maple Street |
| City |  | Boston |
| State |  | MA |

## Probabilistic Analysis of Manual Merges by Users

## Lantern Determined Probability of <br> Manual Merges after 2017 updates



## Manual Merge pairs with 50\% - 75\% Confidence

| Last Match | First Match | DOB Match | Middle Match | Address Match | Total Pairs | Pct Pairs |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| FALSE | FALSE | TRUE | FALSE | FALSE | 19 | 2.64\% |
|  |  |  |  | TRUE | 4 | 0.56\% |
|  |  |  | TRUE | FALSE | 2 | 0.28\% |
|  | TRUE | FALSE | FALSE | FALSE | 4 | 0.56\% |
|  |  |  |  | TRUE | 1 | 0.14\% |
|  |  |  | TRUE | FALSE | 1 | 0.14\% |
|  |  | TRUE | FALSE | FALSE | 392 | 54.44\% |
|  |  |  |  | TRUE | 3 | 0.42\% |
|  |  |  | TRUE | FALSE | 49 | 6.81\% |
| TRUE | FALSE | FALSE |  | FALSE | 1 | 0.14\% |
|  |  | TRUE | FALSE | FALSE | 84 | 11.67\% |
|  |  |  |  | TRUE | 2 | 0.28\% |
|  |  |  | TRUE | FALSE | 3 | 0.42\% |
|  | TRUE | FALSE | FALSE | FALSE | 10 | 1.39\% |
|  |  |  |  | TRUE | 2 | 0.28\% |
|  |  |  | TRUE | FALSE | 3 | 0.42\% |
|  |  | TRUE | FALSE | FALSE | 140 | 19.44\% |
| Grand Total |  |  |  |  | 720 |  |

## Example Manually Merged Pair with low confidence

- While in this case the user may know more about the patient as they have direct patient contact, this match seems unlikely.
- This was either a result of bad data collected by one of the providers, or an incorrect merge.
- This is an opportunity to not just create a better algorithm, but improve data quality and/or train end users.

| Field | Patient A | Patient B |
| :--- | :--- | :--- |
| Last Name | Sample | Sampson |
| Middle Name |  | James |
| First Name | Samuel | Samuel |
| Gender | M | M |
| Date of Birth | $01 / 17 / 2000$ | $01 / 18 / 2000$ |
| Street Address |  | 15 Oak Street |
| City |  | Boston |
| State |  | MA |

## What did we learn?

- Updates from 2017 have significantly helped to alleviate the burden of the manual queue off of users. We accomplished this while staying very accurate, in most cases.
- We were able to identify marginal auto merges and unlikely possible matches, which are an opportunity for the MIIS to re-train.
- Running the analysis for a second year in a row, we were able to use an efficient methodological approach, along with an external tool, to quickly and effectively identify issues (and successes).



## Keys to successful Deduplication Analysis \& Improvements

1. Always follow the DATA!
a) Start with high level trends and narrow down on specific cases. This will translate into the most effective updates.
b) Don't immediately focus on one type of case just because a provider reported it. This may be a valid area to work on, but let the data lead you there.
2. Don't forget the BIG picture!
a) It's easy to get caught up in the details of an individual case. Be careful not to make changes specifically for rare cases that could have a negative effect on the most common matches in the system.

## How can this technology help you?

1) Stand alone tool can be plugged into any database for analysis

- More advanced training: incorporating data from other IIS registries and Public Health projects to create a larger training set will make the tool more detailed and accurate.
- Al Technology likes larger data sets, the more data the better!!

2) Full function deduplication engine - used for real time matching
3) We are now using the Lantern engine built into SSG's case management system, Casetivity, for the following organizations:
a) MA Childhood Lead Poisoning Prevention Program

- 2 million client records
b) MA Early Intervention Program
- System launching 2019



## Thank You AIRA Attendees!

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