Delineating Pediatric Type 1 Diabetes Cohorts with Machine Learning

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What is DKA?

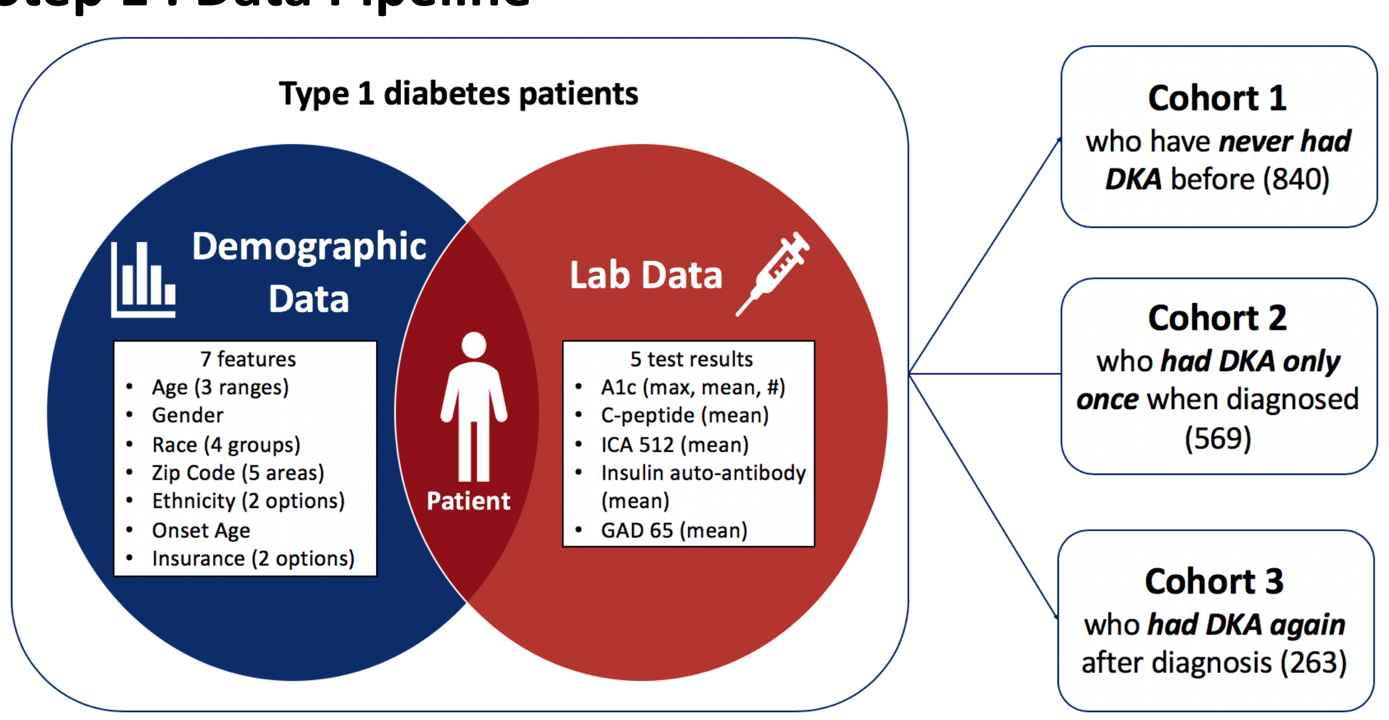
- Diabetic Ketoacidosis (DKA) is a preventable but life-threatening complication from Type 1 diabetes.
- Type 1 Diabetes is an early onset/juvenile diabetes.
  - More than 86,000 children are diagnosed with Type 1 diabetes every year.
- DKA is caused by a lack of insulin that causes high levels of blood acids called ketones.
  - Ketones poison the blood.
  - Can lead to coma and even death.

Data and Methods

Overview

- Collaborative research project with Texas Children's Hospital.
- Utilizes anonymized electronic medical record (EMR) data from pediatric patients.
- Goal is to build a model which can predict whether a type 1 diabetes patient is likely to have DKA in the future.

Step 1 : Data Pipeline

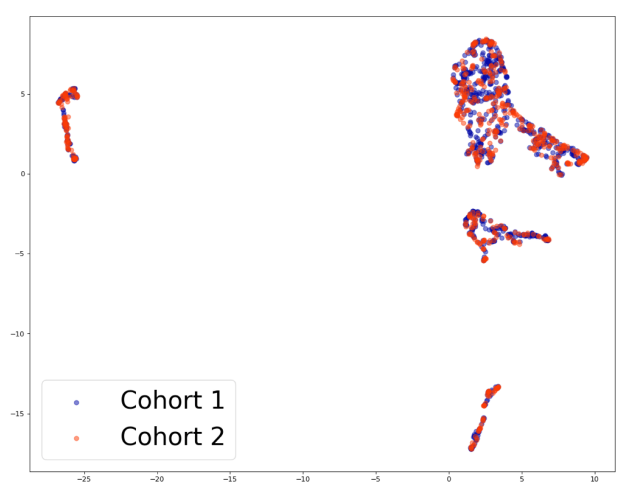


Step 2 : Machine Learning Analysis

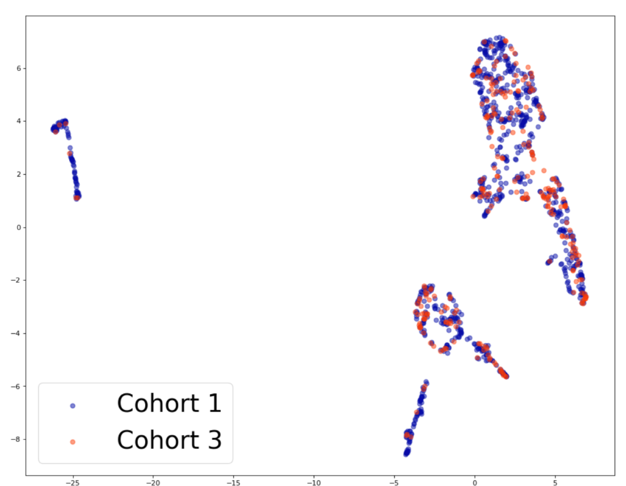
- Build 3 types of models for 3 combinations using lab and demographic data.
  - Logistic Regression, Random Forest, Gradient Boosting
  - 1 vs. 2, 1 vs. 3, 2 vs. 3.
- Plot uniform manifold approximation and projection (UMAP) for each combination, excluding categorical data.
- For each model, calculate area under the curve (AUC) and show important features.

Results

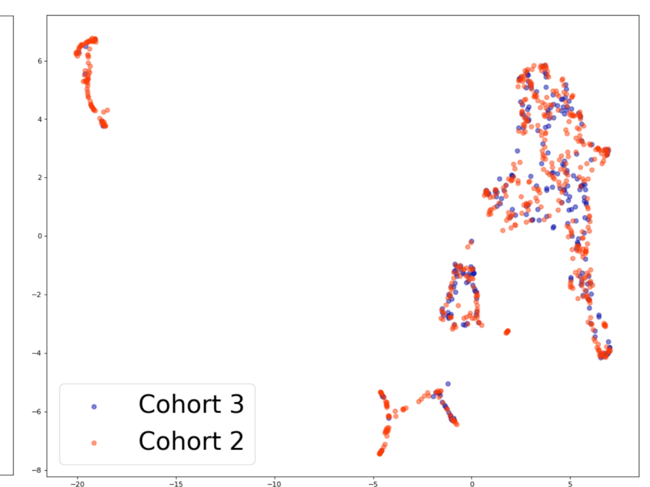
Pairwise Cohort UMAP Visualization



Cohort 1 vs Cohort 2



Cohort 1 vs Cohort 3



Cohort 2 vs Cohort 3

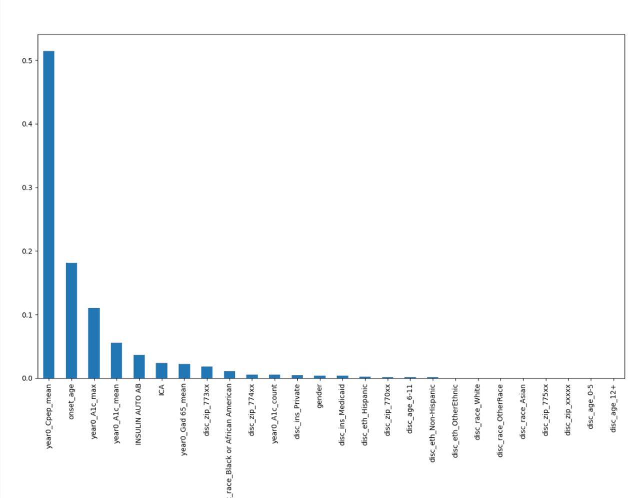
- All UMAP plots depict one large group with ≈3 auxiliary clusters.
- No matter which pair is being considered, the groups are not clearly and cleanly separable.

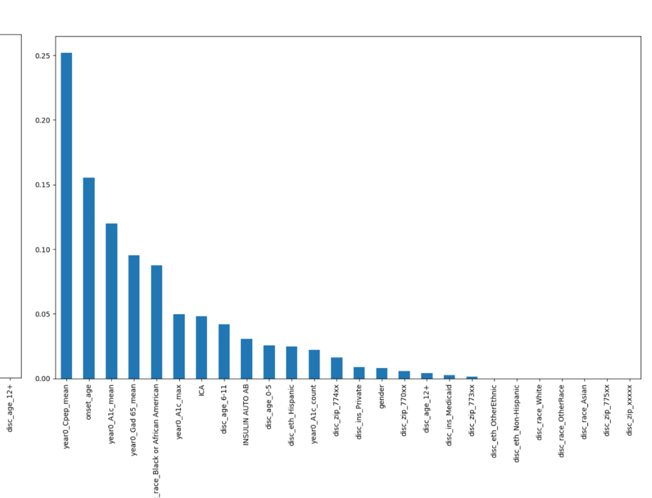
Pairwise Cohort Classification

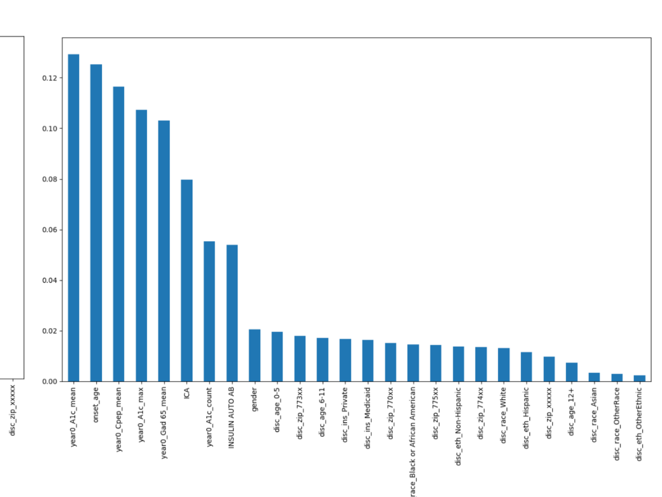
	Model Type	AUC	#1 Feature	#2 Feature	#3 Feature
Cohort 1 vs. Cohort 2	Gradient Boosting	0.80	C-pep mean (Ch1: 0.77 , Ch2: 0.39)	Onset Age (Ch1: 10.06, Ch2: 9.67)	A1c max (Ch1: 10.75, Ch2: 11.71)
Cohort 1 vs. Cohort 3	Gradient Boosting	0.78	C-pep mean (Ch1: 0.77, Ch3: 0.47)	Onset Age (Ch1: 10.06, Ch3: 9.59)	A1c mean (Ch1: 8.35, Ch3: 8.91)
Cohort 2 vs. Cohort 3	Gradient Boosting	0.66	GAD 65 mean (Ch2: 52.34, Ch3: 19.25)	A1c mean (Ch2: 8.80, Ch3: 8.91)	C-pep mean (Ch2: 0.39, Ch3: 0.47)

- C-pep mean, onset age, and A1c mean/max are generally the most predictive features for cohort classification.
- C-pep mean values show graded separation for each cohort consistent with clinical expectations.
- For the Cohort 2 vs. Cohort 3 model, GAD 65 mean was the most important.

Important Features for Each Combination


Cohort 1 vs. Cohort 2


Cohort 1 vs. Cohort 3


Cohort 2 vs. Cohort 3

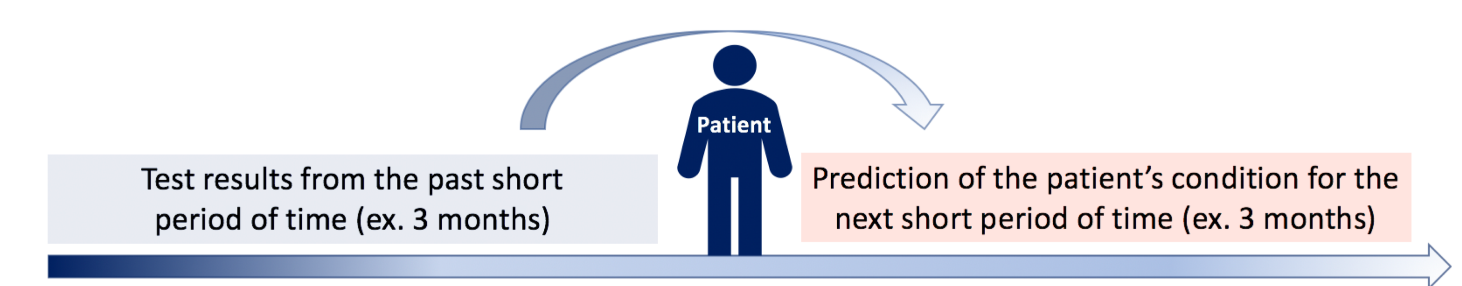
- Lab data is relatively more important than demographic data.
- Models separating cohorts 2 and 3 utilize more features than models separating the other cohorts.

Discussion and Conclusion

- UMAP plots suggest a generally consistent structure across cohorts.
- UMAP plots demonstrate the difficulty of classifying each cohort.
- Cohorts 2 and 3 are the least separable by these methods.
  - Both have DKAs in their first year after diagnosis, the only data used in this analysis.
- Each cohort has differing numbers of patients; balancing training sets may yield improvements.
- Additional data from BMI and blood pressure, as well as encounter data, wasn't included in this analysis.
- It is still unclear what features shape the subsets in each UMAP cluster.
- The features defining each cohort make clinical sense, and could help support physicians with diagnosis / prognosis

Future Research

1. Create ensemble models to improve performance.
2. Investigate UMAP clusters, revealing their possible clinical significance (i.e. are they clinically relevant subgroups of Type 1 diabetes).
3. Build a time-sensitive model, operating over the full range of time-indexed data we have available.



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