Medi chal

Synthetic Medical Data Generation

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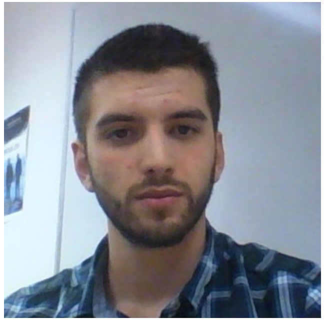
The Team



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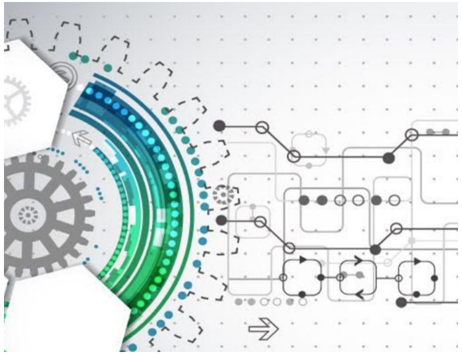
Objectives

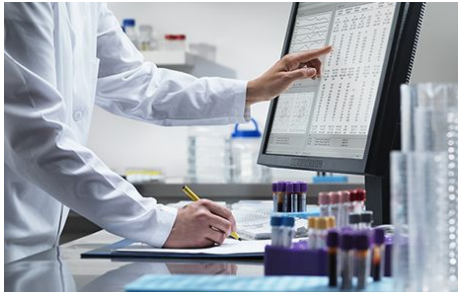
Training

students in health data analytics



Benchmarking new algorithms

Advancing medical research



Method

- Repo: https://github.com/Didayolo/medi-chal/tree/master/
- Data:
  - Target = OPTUM LABS
  - Practice = REPO/data (MIMIC data + classical ML datasets, all in standard format + artificial data)
- Generative models: REPO/code/generators
- Evaluation:
  - ID notebook: REPO/notebooks/auto_ml/ID_notebook.ipynb
  - Comparison notebook: REPO/notebooks/auto_ml/comparison_notebook.ipynb

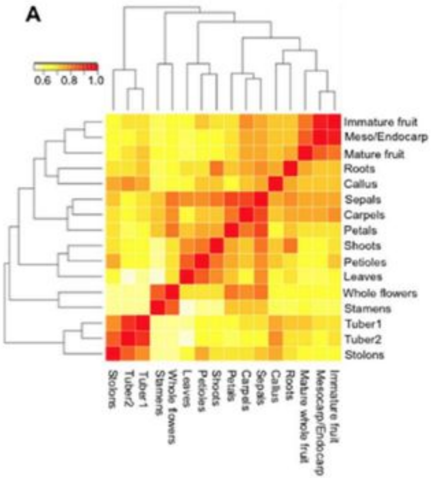
Requirements: retain utility and protect privacy

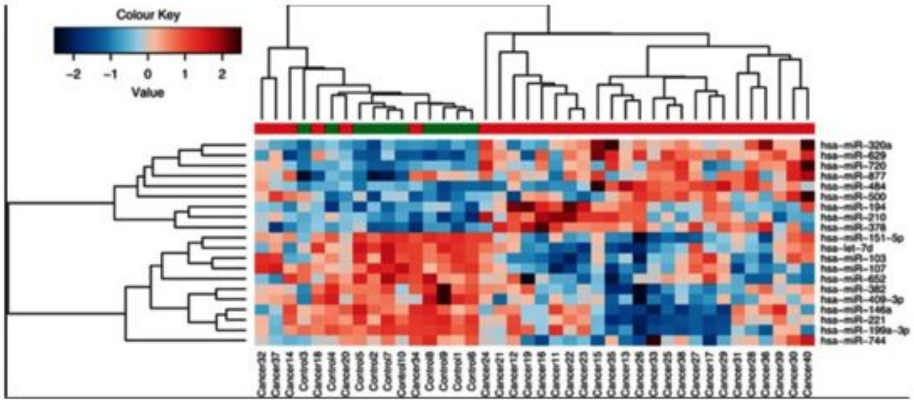
- Utility
  - **Distributions** similar (Similar marginals and multivariate dependencies)
  - **Application** results similar

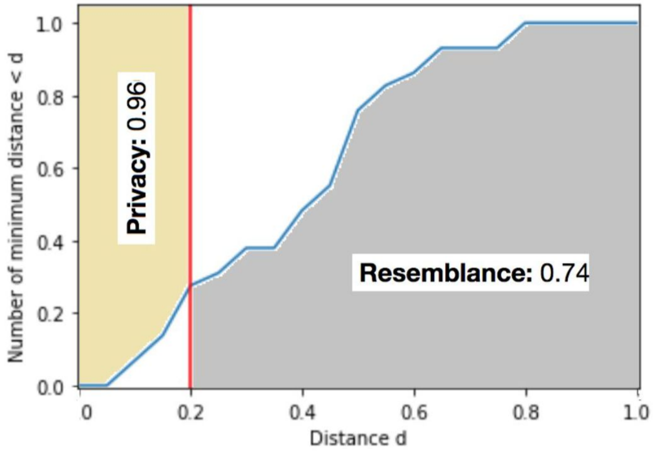
- Privacy
  - **Identity** hidden
  - **Sensitive information** protected

A quick tour

- [ID notebook]







- [Comparison notebook]

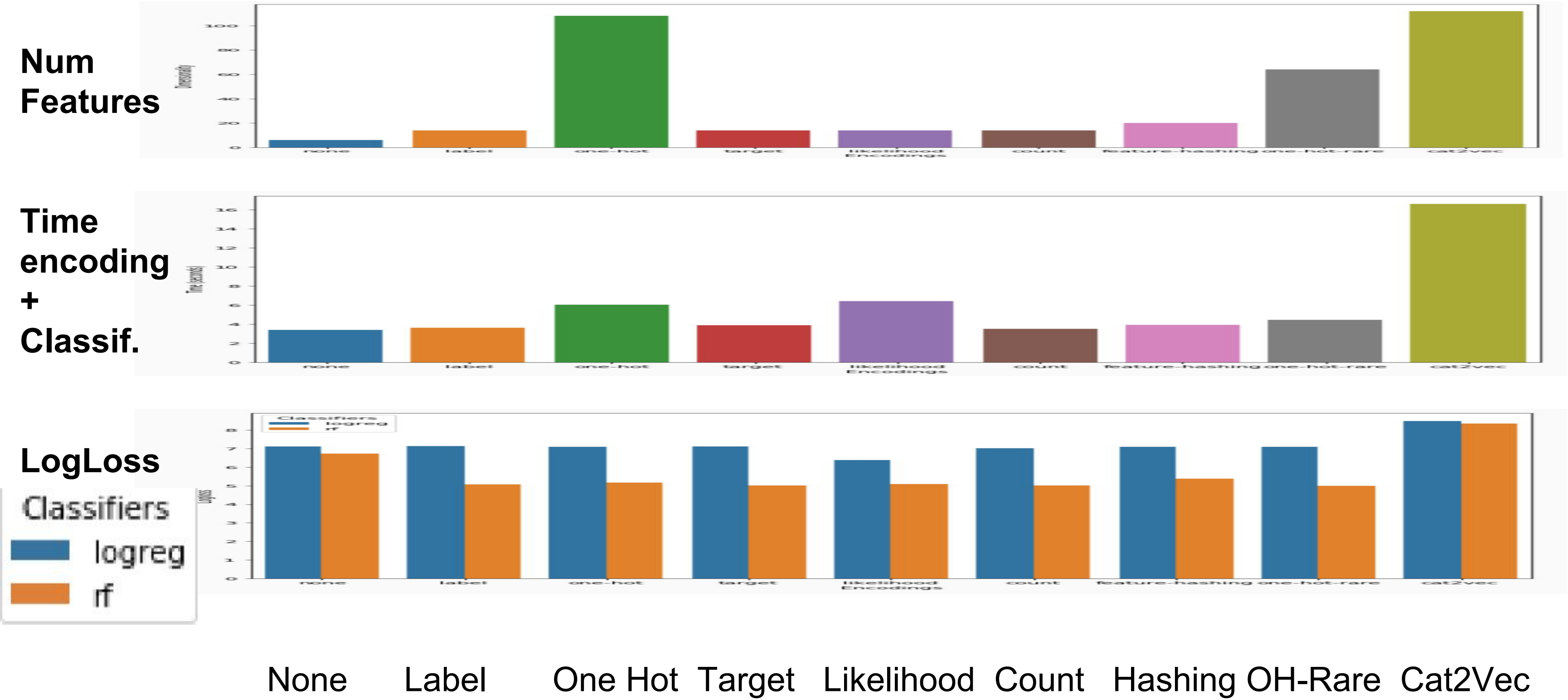
Modeling workflow

1. **Pre-processing:** privacy sanitizing, encoding categorical variables, imputing missing values, etc. [ID notebook]
2. **Modeling**: [Generator library]
   a. **Classical statistics** (e.g. Parzen windows and other kernel methods, multivariate Gaussians).
   b. **Machine Learning** (e.g. imputation of missing values with RF, Generative Adversarial Networks -- GAN, Causal generative networks).
3. **Post-processing:** privacy tuning, marginal distribution back-fitting (Copula inspired); restore categorical variables.
4. **Quality control**: Utility and privacy [Comparison notebook]

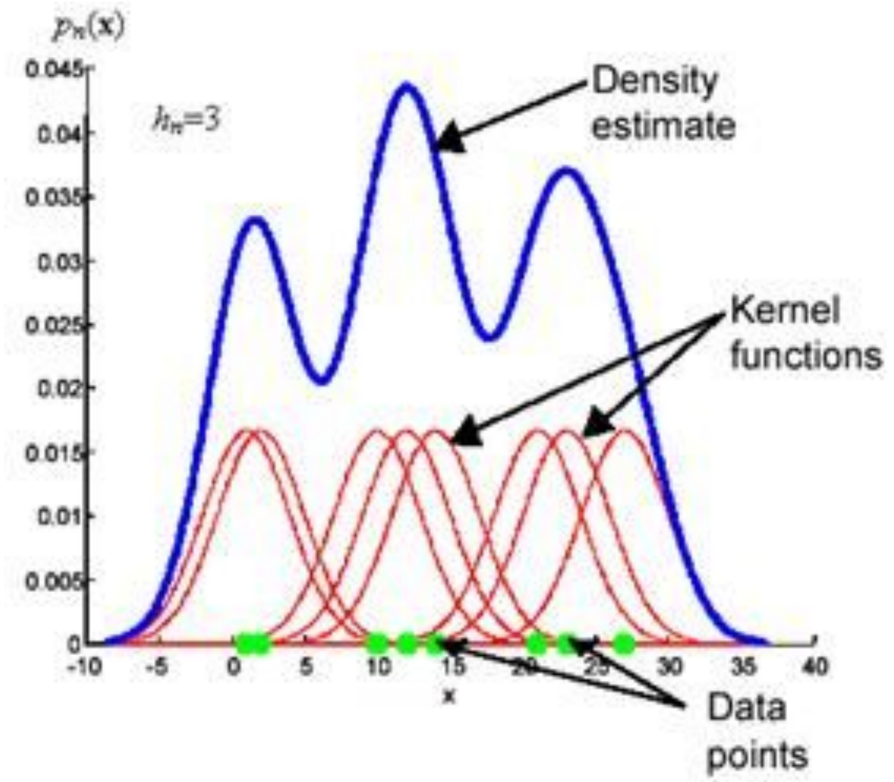
1. **Preprocessing:** Encoding categorical variables

- None (remove categorical variables)
- Label (arbitrary numerical value)
- One hot (binary encoding)
- Feature hashing
- Mean target value
- Likelihood
- Frequency
- Cat2vec: DL embedding

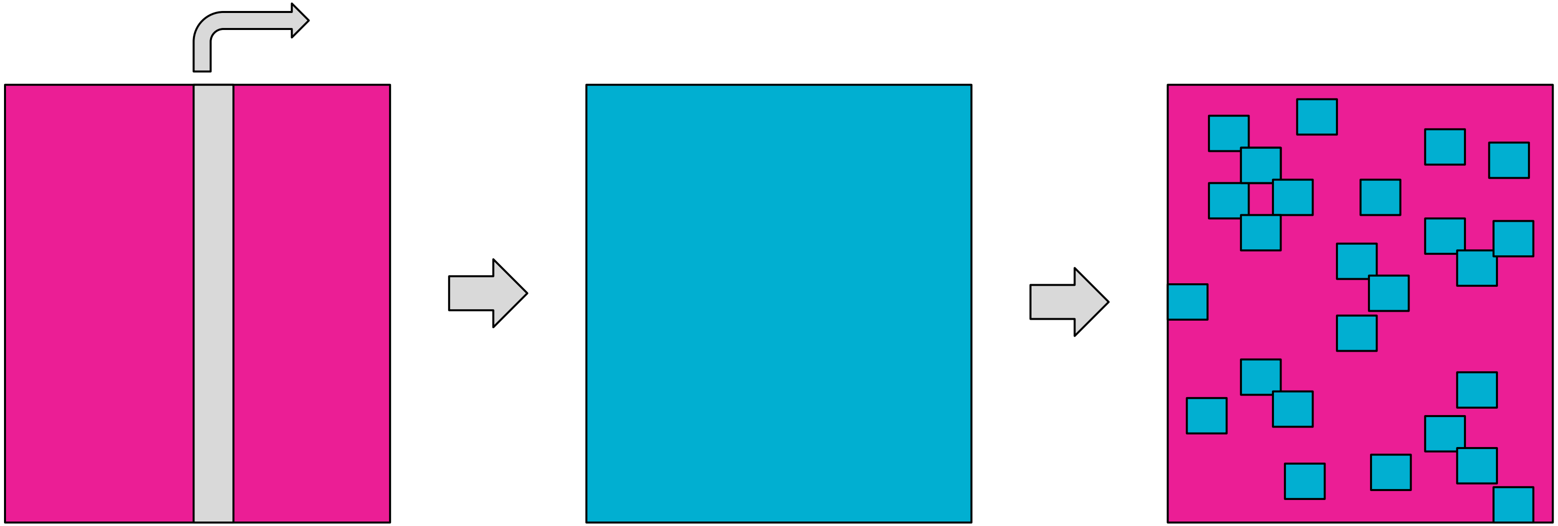
Categorical variables: Comparison of encodings



2. Modeling: Parzen windows



2. Modeling: Missing values imputation with RF



ORIGINAL DATA

(1) Build predictors of one column from the others..

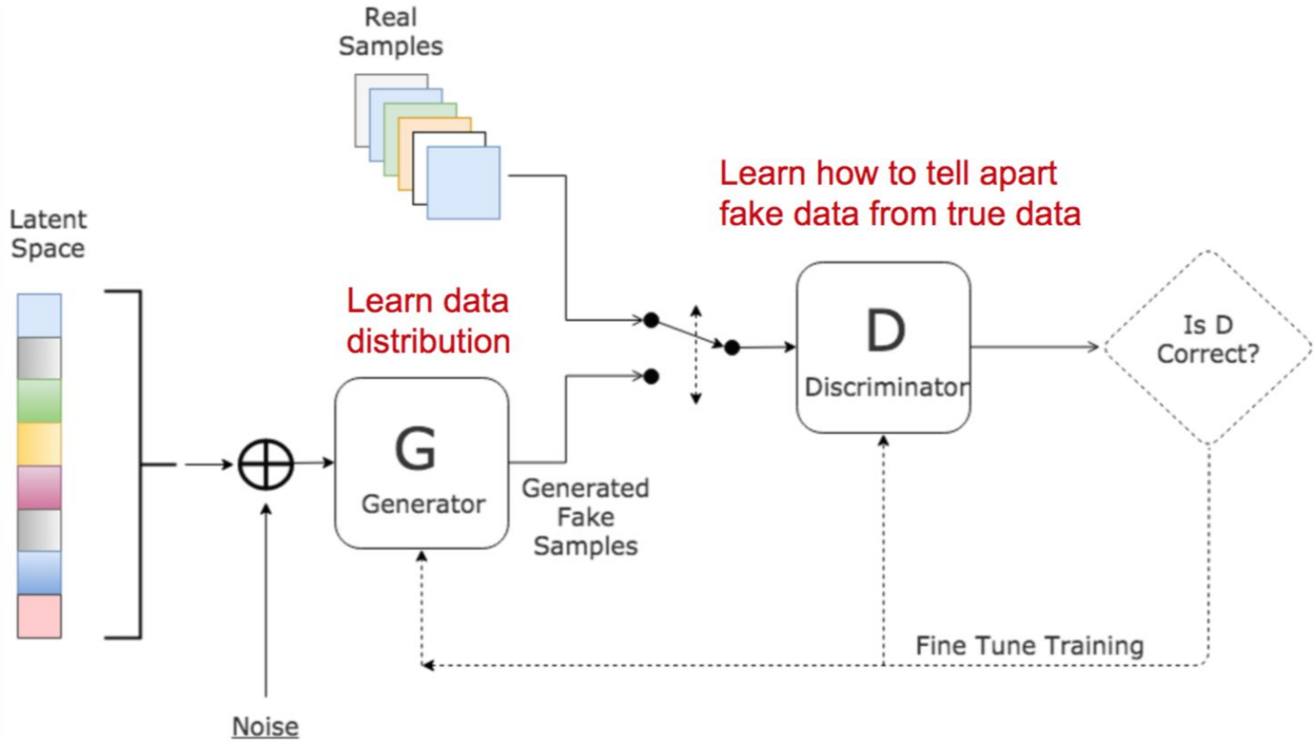
PREDICTED DATA

(2) Make a matrix of predictions.

SYNTHETIC DATA

(3) Mix original and predicted data randomly in a certain proportion p.

2. Modeling: GAN (Generative Adversarial Networks)



Two flavors: MedGAN (Andrew) and SAM (Diviyan)

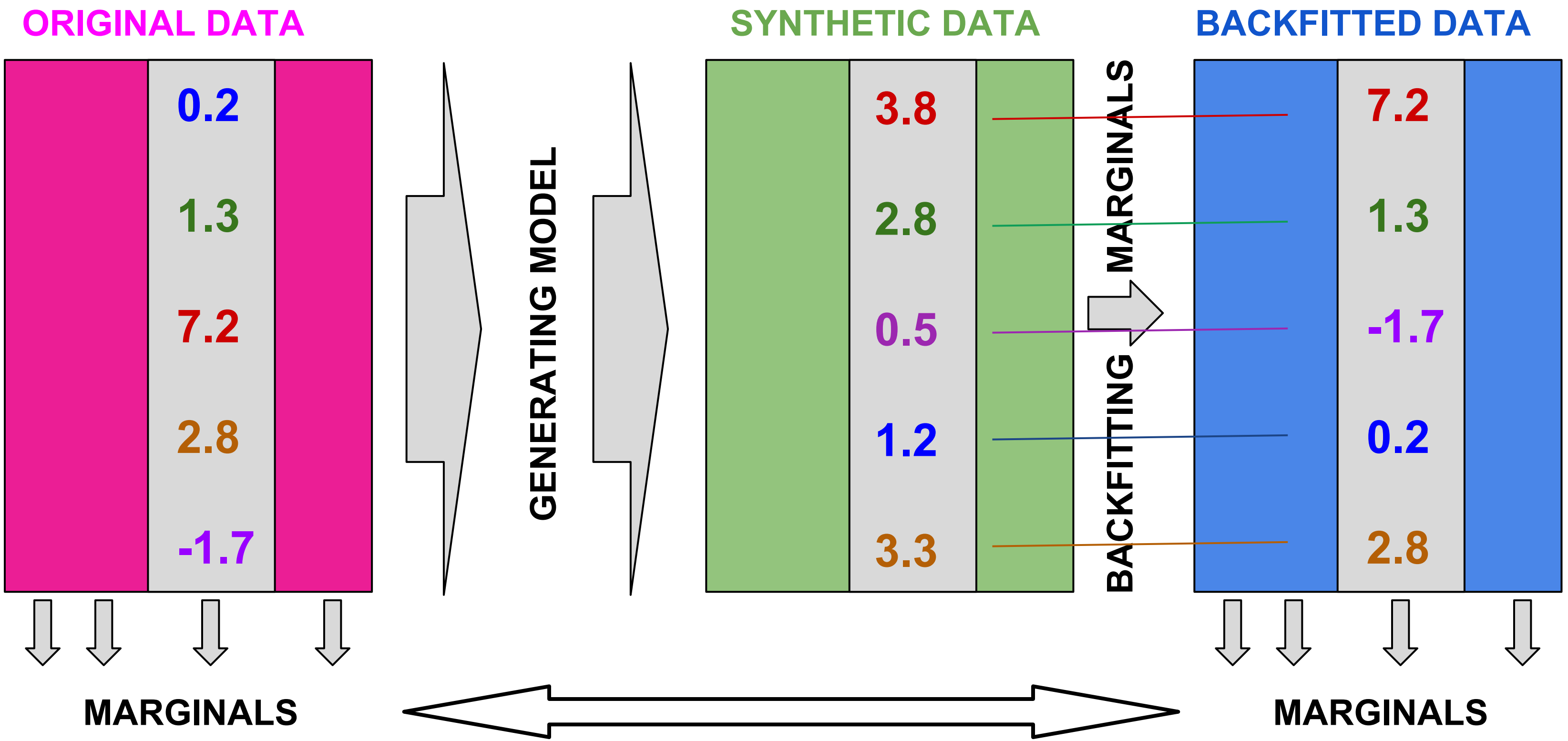
2. Modeling: Copula

Copula = multivariate distribution with uniform marginals

Sklar's theorem = Every multivariate distribution can be expressed in terms of its marginals and a copula.

Procedure Copula modeling:
> Make marginals uniform (replace variables by their rank)
> Model the distribution
> Back-fit the marginals to the original marginals

3. Post-processing: Backfitting marginals (Copula trick)

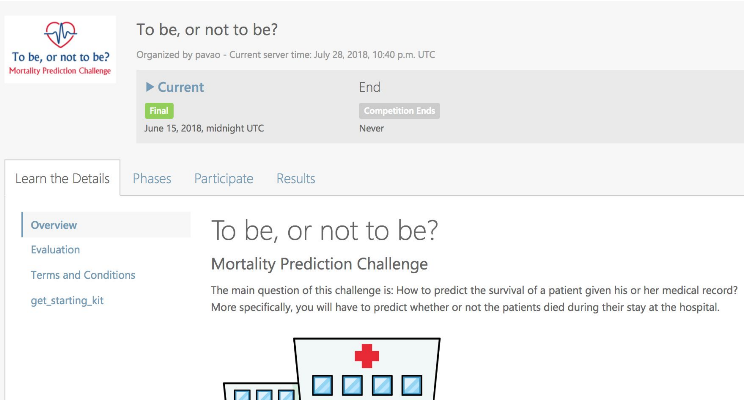


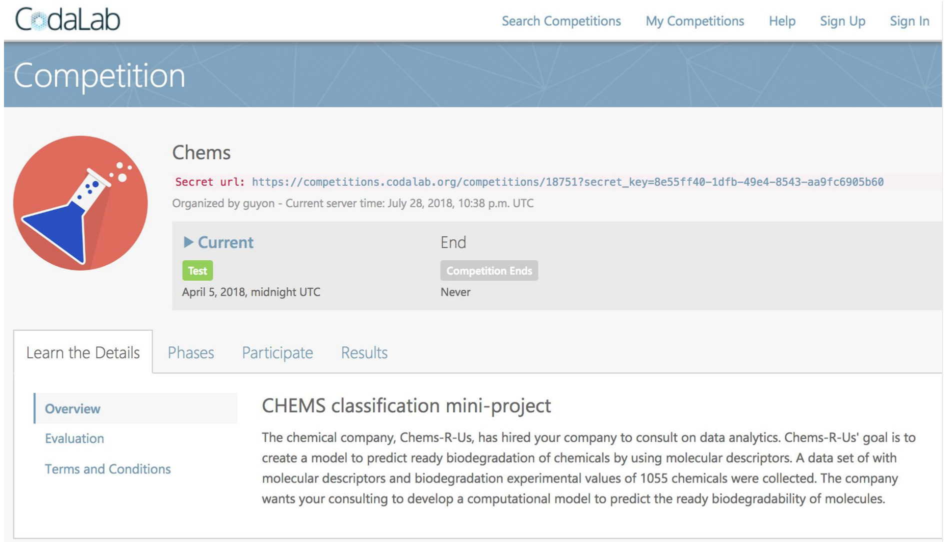
On-going work

Systematic study to compare **Utility** and **Privacy**.

Methods / Datasets	Pazen (or other kernel method)	Gaussian multivariate	RF multiple imputation	GAN(s)
Iris				
Boston housing				
Adult (census)				
Mimic				

Challenge organization





- Chems: Predict ready biodegradation of chemicals by using molecular descriptors.
- Mortality: Predict the survival of a patient given his or her medical record using synthetic MIMIC data.
- Chems 2: with feature selection (in preparation)
- Survival analysis (in preparation)

Conclusion

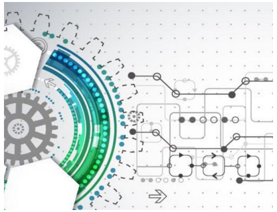
- With our synthetic data we already started

training students in health data analytics

- We are working on:

- improving data quality and

- designing ML challenges for students and researchers.



- Using synthetic data for discovery is further

  down the road: Utility / Privacy tradeoff.