**Objectives**

Organ transplants
- Therapy of choice for patients with end-stage diseases!
- National Kidney Foundation: 121,678 people waiting for lifesaving organ transplants in the U.S. as of 1/11/2016!

Challenges
- Post-operative complications: infection, rejection and malignancy (Huynh 2014).
- Complications are highly dependent on the features of both recipients and donors!
- Proper recipient-donor matching requires accurate pre-operative survival analysis \( \rightarrow \) very little domain knowledge!

Our goal \( \to \) learn recipient-donor compatibility from the electronic health record data (EHR)!

**State-of-the-Art**

Current clinical practice
- Donor Risk Index (DRI) (Feng 2006)
- Risk-Stratification Score (RSS) (Sorror 2007)
- Index for Mortality Prediction After Cardiac Transplantation (IMPACT) (Weiss 2011)

Drawback of clinical risk scores:
- Expert-based, no rigorous validation.
- Ignores the heterogeneity of the recipient-donor characteristics.

Need a data-driven predictive model that discovers subgroups of “similar patients”!

**Related Machine Learning Algorithms**

- Ensemble Methods (Kuznetsova 2014)
- Clustering Methods (Sontag 2016)
- Decision Tree Methods (Strobl 2009)

**Algorithm**

- **Training set:** transplants before 2010.
- **Testing set:** transplants after 2010.
- Our algorithm discovers 7 clusters (phenotypes) for the heart transplant recipient-donor pairs.

**Experiments**

- Gains in the number of patients for whom the PPV is 90% PPV are:
  - 298 compared to DeepBoost.
  - 1,841 compared to RSS.

**Conclusions**

- The outcomes of organ-transplant surgeries depend crucially on the individual traits of recipients and donors.
- We developed a personalized prognostic tools that learns a tree of predictors, the output of which is a set of recipient-donor feature clusters (phenotypes), and a predictive model customized for every cluster. The performance of our algorithm outperforms state-of-the-art clinical risk scores and other machine learning algorithms.