



# RAPID LIFE-CYCLE IMPACT SCREENING FOR DECISION-SUPPORT AT EARLY STAGE CHEMICAL DESIGN

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Environmental Science & Technology; In Revision

#### About me



- Third year PhD Student
   Prof. Sangwon Suh and Prof. Arturo Keller
- Life-Cycle Assessment for Chemicals; Life-Cycle Inventory Database; Machine Learning; Chemical Toxicity Prediction.



□ Chemical Life-Cycle Collaborative (CLiCC) with US EPA.

# Background – The CLiCC Project CHEMICAL LIFE CYCLE



# Background – Predictive LCIA

- There are more than 100 million chemicals in CAS database;
  - 15,000 new chemicals are being added everyday.
- In many cases, we don't have the necessary data to build LCI for chemicals;
- □ Alternative path to estimate LCA indicators.
  - e.g., CED, GWP and Eco-indicator;
  - Estimates the indicators with molecular structure information using machine learning models.





## Background – Predictive LCIA

 Chemical structure is correlated with chemical properties and impacts;



 Linear regression model has been widely used to approximate chemical impact;

The predictive power is restricted.

- Nonlinear model shows better predictive power
  - Artificial Neural Networks (ANNs) outcompetes linear regression model in estimating life-cycle indicators for chemicals.



...than this

#### Background – Deep ANNs

□ ANNs model becomes very popular because of the concept "deep learning"



# Highlights of This Study

Estimate the life-cycle impact indicators for chemical

- Use deep Neural Networks model;
- Use high dimensional molecular structure descriptors;
- Model structures were tuned;
- Model Applicable Domains (AD) were measured;
- What we learnt from this study.



#### Method – Data

166 chemical LCI data were collected from Ecoinvent v3.01

- 10 chemicals were used as testing set
  10% of the rest 156 chemicals were validation set
- About 4,000 molecular descriptors were generated by software Dragon 7.
- Principle component analysis was used to reduce the dimension of the descriptors.



#### **Results – Acidification Model**



#### **Only Test Set**

All Chemical We have...



Reported Value (mole H+ eq.)

#### **Results – Model Training**



### Model Applicable Domain

- Query chemicals that have higher structural similarity with the training data are likely to have higher prediction accuracy.
- Accuracy could be measured depending on if this chemical falls into the applicable domain.
  - MRE of test chemical inside AD: 40%
  - MRE of test chemical outside AD: 85%



### Model Demo on Test Data

2,4-Dichlorophenol

- TRACI, Acidification: 1.32 (moles of H+-Eq);
- Our model estimates: 1.27 (moles of H+-Eq);
- Uncertainty according to AD: Low

Hexafluoroethane

- TRACI, Acidification: 6.8 (moles of H+-Eq);
- Our model estimates: 4.6 (moles of H+-Eq);
- Uncertainty according to AD: High





- We are able to predict three mid-point indicators (CED, Acidification, GWP) and three end-points indicators (EI99, Human health, Ecosystem quality);
- $\Box$  The cross-validated models show good predictive power on testing data (R2 > 0.7);
- Model applicable domain measurement can indicates the uncertainty of the prediction;
- □ The end-point indicators require higher complexity of the model.



More training data will always be beneficial;

 It's hard to tell the contribution of each input descriptors;

□ This field is developing very fast.

















This research is funded by U.S. EPA - Science To Achieve Results (STAR) Program Grant #<mark>83557907</mark>





