



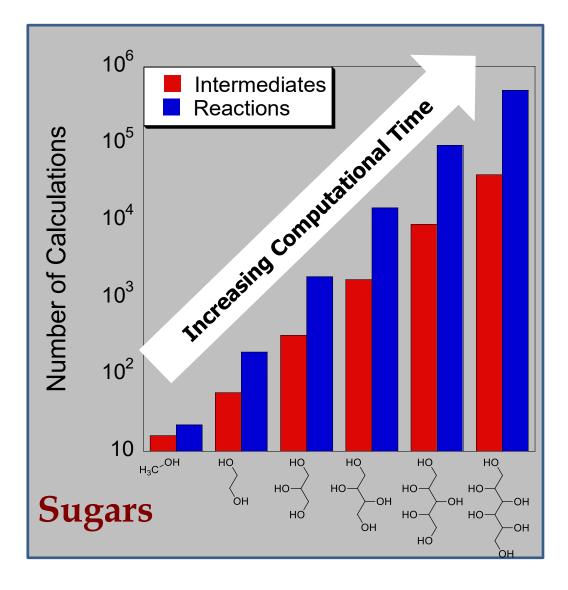
Theory, Applications, and Tools for Multiscale Kinetic Modeling: Parameterizing Large Models

D. Vlachos and G. R. Wittreich





Modeling Reactions of Large Molecules is Challenging

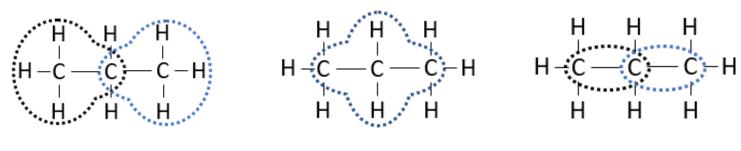


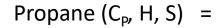
- Combinatorial explosion in number of calculations for first-principles (DFT) calculations
- Semi-empirical methods can potentially parametrize relevant species and reactions instantaneously
- Major advances in systematic development of semi-empirical methods and understanding of errors





Method: Group Additivity^{1,2}

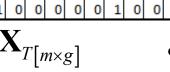


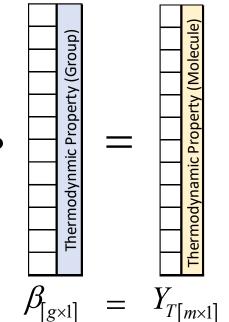


2 x C(C)(H) ₃	+
--------------------------	---

$$1 \times C(C)_2(H)$$

	Groups												
	2	0	0	0	0	1	0	0	0	0	1	0	0
	1	0	2	0	0	0	0	0	0	0	0	0	0
	2	0	0	0	1	0	0	0	0	0	1	0	0
es	0	0	0	0	2	0	0	0	0	1	0	0	2
Training Molecules	0	0	0	2	0	0	0	0	2	0	0	1	0
1016	0	0	2	2	0	0	1	0	0	1	0	2	2
50	1	1	0	0	0	0	0	0	1	0	0	1	0
ij	0	1	0	0	0	0	0	0	2	1	0	0	0
Tra	2	2	2	0	0	0	2	0	0	0	1	1	0
	2	0	0	0	0	0	1	0	0	0	1	0	0
	2	1	0	0	0	0	0	0	1	0	2	0	0
	0	0	0	1	0	0	0	0	0	1	0	0	1





$oldsymbol{eta}_{\![g imes l]}$	$=\mathbf{X}_{T[m\times$	$[g] \cdot Y_{T[m \times 1]}$
$P_{[g \times 1]}$	$-T \mathbf{L}_{T[m \times m]}$	$[g] T[m \times 1]$

$$\beta_{[g\times 1]} = \left(\mathbf{X}_{T[g\times m]}^{'} \cdot \mathbf{X}_{T[m\times g]}\right)^{-1} \cdot \mathbf{X}_{T[g\times m]}^{'} \cdot Y_{T[m\times 1]}$$

$$\hat{\sigma} = \sqrt{\frac{\sum \left(\mathbf{X}_{T[m \times g]} \cdot \boldsymbol{\beta}_{[g \times 1]} - \boldsymbol{Y}_{T[m \times 1]}\right)^{2}}{m - g}} \quad \begin{vmatrix} \hat{\sigma}_{C_{p}} = 0.12 - 0.73 \ cal/mol \cdot \boldsymbol{K} \\ \hat{\sigma}_{H} = 4.53 \ kcal/mol \\ \hat{\sigma}_{S} = 2.07 \ cal/mol \cdot \boldsymbol{K} \end{vmatrix}$$

$$\hat{\sigma}_{C_P} = 0.12 - 0.73 \ cal/mol \cdot K$$

$$\hat{\sigma}_{H} = 4.53 \ kcal/mol$$

$$\hat{\sigma}_{S} = 2.07 \ cal/mol \cdot K$$

¹ Benson, S. W. et al. (1969), Chemical Reviews

² Kua, J. and Goddard, W. A. (1998), J. Phys. Chem. B

³ https://github.com/VlachosGroup/PythonGroupAdditivity Gu et al. (2018), Reaction Chemistry & Engineering.

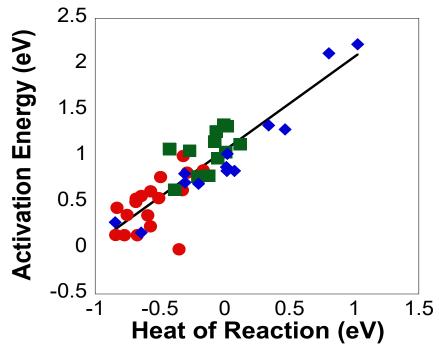




Method: Machine Learning

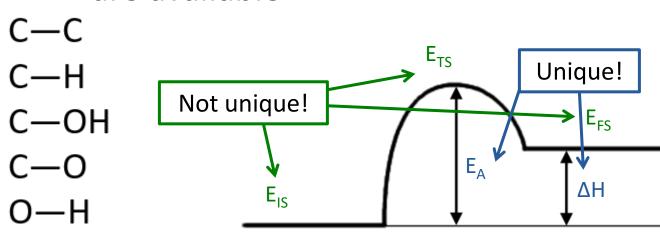


Brønsted-Evans-Polanyi (BEP) Relationships¹



$$\Delta E_{a,i} = \omega \Delta H_{rxn,i} + \Delta E_0$$

- BEP relationships can be used as they enable the prediction of reaction barriers from the heat of reactions for an entire homologous series of reactions
- BEPs for common homologous series are available





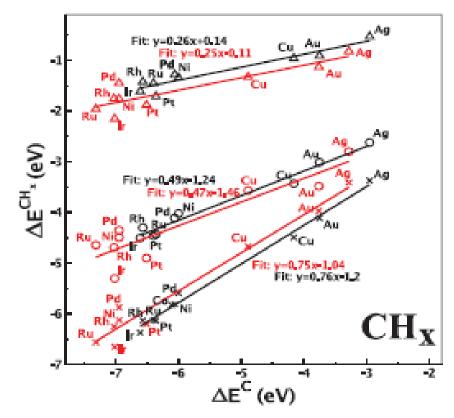


Linear Scaling Relationships (LSRs) for Metal Cats

$$Q^{AH_x} = \gamma Q^A + \beta, \quad \gamma = \frac{x_{\text{max}} - x}{x_{\text{max}}}$$

Simple/Small Molecules: CHx, NHx, OHx, SHx,...

- They work well when AHx binds on catalysts with the same binding mode, e.g., bridge binding
- Impact: By computing Q_A on a new catalyst, e.g., bimetallic, you can compute Q_{AHx}, so one saves some comps



Polyatomic/Multidentate Adsorption: Extended LSR

$$Q_{i,new} = Q_{i,ref} + \sum_{j=1}^{n} \gamma_{i,j} \left(Q_{new}^{ref species, j} - Q_{ref}^{ref species, j} \right)$$





Summary of Semi-empirical Methods

- Group additivity estimates species thermochemistry for large molecules and mechanisms
 - Once the groups have been identified via graph theory and the values estimated, these can be used for any mechanism on the same catalyst
 - Reaction thermochemistry is estimated from species thermochemistry
- Extended linear scaling relations can be used to estimate species thermochemistry on a new catalyst from a reference catalyst
- BEPs or transition state scalings can be used to estimate reaction barriers from thermochemistry
 - BEP is applied to the entire homologous series; a few DFT data to estimate and information is then transferable to all reactions of the same family
 - Tacitly assumed that the BEP holds among catalysts for the same chemistry
- These relations are linear; machine learning can be used to improve accuracy, identify descriptors, e.g., groups in GA, and capture nonlinear effects