

Automation gap in chemical synthesis

Advances in laboratory automation promise to decrease the manual effort of synthesis, but determining *how* to synthesize a compound still requires expert chemist knowledge



Hwang⁸ and Coley⁹ et al., *Chem. Comm.* 2017

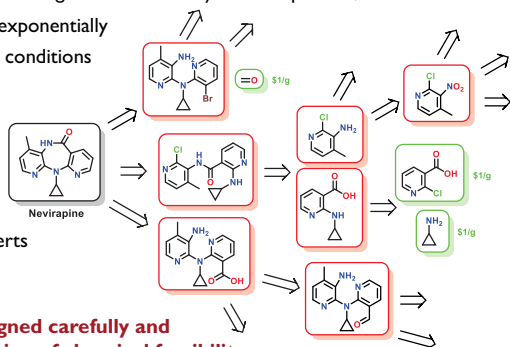


Godfrey, Masquelin, and Hemmerle, *Drug Discov. Today* 2013

Computer-aided synthesis planning (CASP)

Pathways can be generated through recursive *retrosynthetic* expansion, but...

- The search space grows exponentially
- Suggestions must include conditions in addition to structures
- Disconnection rules are imperfect and may not be chemically feasible
- Detecting and reducing these false positives is challenging, even for experts
- No system has achieved wide-spread adoption



Pathways must be designed carefully and with explicit consideration of chemical feasibility

Extensible framework for pathway design



Key elements include:

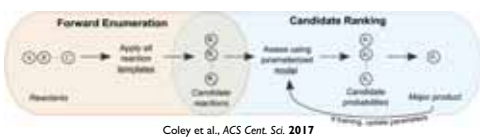
- Candidate precursor generation with awareness of chirality
- Reaction condition recommendations
- Feasibility assessment through explicit prediction of reaction outcomes

Coley et al., *Acc. Chem. Res.* 2018

Validating via prediction of reaction outcomes

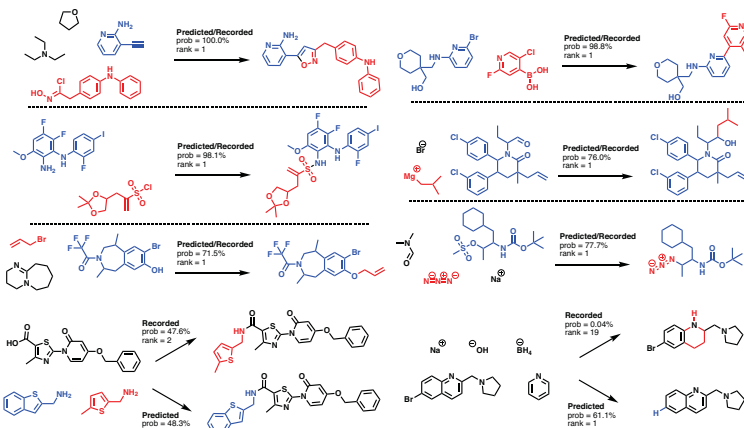
Retrosynthetic suggestions can be evaluated by solving the reverse problem: Given a set of reactants (and conditions), what is the major product?

[v1] Template-based, hybrid method



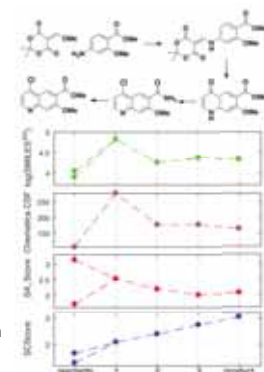
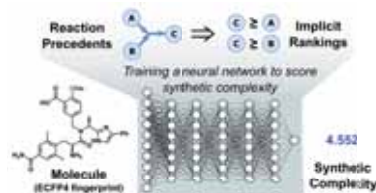
Coley et al., *ACS Cent. Sci.* 2017

- Reaction templates define scope of possible outcomes
- Neural network model ranks candidates



Guiding a retrosynthetic search: SCScore

To overcome combinatorial explosion, the search is focused along promising directions likely to lead back to purchasable compounds

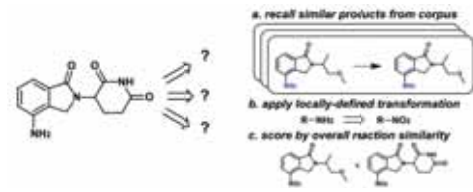


Published reaction data can be used to learn a synthetic complexity score to quantify if progress is being made in a synthetic step

Coley et al., *J. Chem. Inf. Model.* 2018

Making focused retrosynthetic suggestions

An automated procedure can codify the workflow a beginner chemist might undertake when synthesizing a novel molecule: *look for similar compounds*



Model	top-n accuracy (%)				
	1	3	5	10	50
Liu et al. baseline	35.4	52.3	59.1	65.1	68.6
Liu et al. seq2seq	37.4	52.4	57.0	61.7	65.9
Similarity (this work)	52.9	73.8	81.2	88.1	91.8

- Disconnections proposed based on analogy
- Rare transforms need not be excluded
- Extends to multi-step planning
- Outperforms previous neural translation study

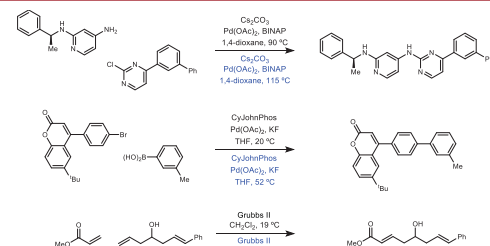
Coley et al., *ACS Cent. Sci.* 2017

Recommending reaction conditions

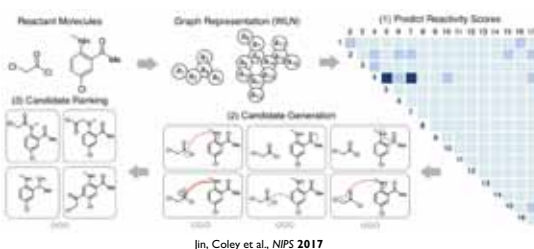
A recommender system suggests conditions for novel reactions

- Compatibility implicitly considered
- Close agreement to literature on test set

Gao, Struble, Coley et al., submitted



[v2] Template-free, fully-learned method



Jin, Coley et al., *NIPS* 2017

- Template-free method overcomes bottleneck of template application
- Achieves higher accuracy and expert-level performance

USPTO-15K				
Method	Cov.	P@1	P@3	P@5
Coley et al.	100.0	72.1	86.6	90.7
WLN	90.1	74.9	84.6	86.3
WLDN	90.1	76.7	85.6	86.3

USPTO				
Method	θ	P@1	P@3	P@5
WLDN	3.2M	79.6	87.7	89.2
WLDN (*)	3.2M	83.9	93.2	95.2

Quantitative performance. Prediction at ranks 1, 3, 5. (*) denotes that the true product was added if not covered during previous stage

Human benchmarking

