

## Invited Lecture

**Exploring the cocrystal network in the Cambridge Structural Database****T.E. de Vries<sup>1</sup>, H. Meekes<sup>1</sup>, P. Tinnemans<sup>1</sup>, E. Vlieg<sup>1</sup>, R. de Gelder<sup>1</sup>**<sup>1</sup>*Radboud University, Institute for Molecules and Materials, Solid State**Chemistry, Heyendaalseweg 135, 6525 AJ Nijmegen, The Netherlands**r.degelder@science.ru.nl*

The physico-chemical properties of active pharmaceutical ingredients, agrochemicals, and other useful chemicals can be altered and optimised by forming multi-component crystals, such as salts, solvates and cocrystals. Discovering suitable multi-component crystals, especially cocrystals, is time-consuming and labour-intensive. The Cambridge Structural Database (CSD) contains a massive number of cocrystals that can be used to construct an extensive network of coformers [1]. This network contains predictive power for discovering new cocrystals by applying link-prediction methods [2,3] or artificial neural networks [4].

It is possible to bipartise the entire CSD cocrystal network, which shows the remarkable global complementarity that is present in the network structure [5]. Bipartisation also reveals 'universal' coformers, that do not conform to the bipartite nature of the network, and makes identification of anticomunities of coformers possible. The accuracy of network-based cocrystal prediction can be improved by applying bipartisation to the CSD cocrystal network prior to link prediction. Moreover, combining bipartisation with the Multi- Steps Resource Allocation (MSRA) measure [6] outperforms the earlier applied scoring functions for link prediction [7].

Iteratively applying link prediction, cocrystal screening and network updating demonstrates that saturation of the local network around a target compound eventually diminishes the returns of the method. At the same time, it demonstrates that a steadily expanding CSD database is of great value to the discovery of new multi-component crystals.

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