



the intersection substructures tend to be more common and therefore more useful for the prediction algorithm. Table 1 also includes the number of unique substructures used in the Open Babel predictor.

**Table 1. Unique Substructures in Each Library and Percent Coverage of CSD Library**

	total	organic	metal–organic
CSD	697813 (100%)	182075 (100%)	515738 (100%)
Free	446121 (9%)	122909 (22%)	323212 (4%)
Open Babel	2236	2236	0

**Table 2. Fraction of Test Structures That Were Successfully Predicted**

	organic (%)	metal–organic (%)
COSMOS (Free library)	99	90
Open Babel (OB library)	98	85
RDKit	88	23
Balloon	89	58

**Table 3. Mean RMSD (and Standard Deviation) in Å of Predicted Organic Molecule Structures for Different Structure Prediction Algorithms (rows) and Substructure Libraries (columns)**

	CSD	Free	OB	none
COSMOS	1.04 (0.88)	1.16 (0.88)	—	1.24 (0.92)
Open Babel	1.39 (0.96)	1.39 (0.97)	1.39 (0.97)	1.65 (0.98)
RDKit	—	—	—	1.36 (0.91)
Balloon	—	—	—	1.47 (1.05)

## EXPERIMENTS

We compared the coverage, accuracy, and speed of COSMOS to three other freely available algorithms for structure prediction: Open Babel, RDKit, and Balloon. Predicted 3D structures were compared to ground-truth 3D structures from the CSD, both for a test set of organic molecules and a test set of metal–organic molecules. The test sets were constructed by randomly sampling 10,000 organic and 10,000 metal–organic molecules from the CSD and then removing molecules with any substructures contained in either of the data-derived libraries. This is necessary because both the test sets and the libraries contain structures from the same published crystallography data. Substructures were considered equivalent if they had the following three

properties: (1) at least seven heavy atoms, (2) the same isomeric SMILES code, and (3) an RMSD less than 0.001 Å. After removing these, our clean test sets consisted of 9184 organic molecules and 9595 metal–organic molecules.

COSMOS relies on the OEChem software library,<sup>13,14</sup> so the test molecules were represented as OEChem isomeric SMILES for COSMOS, RDKit, and Balloon. However, the Open Babel toolkit has its own functions for computing isomeric SMILES, so the Open Babel predictions were based on Open Babel isomeric SMILES computed directly from the 3D test structures.

Open Babel predictions were made using the OBBuild method and optimized using the UFF molecular force field<sup>15</sup> for 500 steps. Because the Open Babel predictor uses a substructure library, we tested whether the predictor accuracy would increase with additional substructures from the crystallography data sources. As in the original Open Babel substructure library, the augmented libraries were sorted in decreasing size so that large substructures were matched first. Canonical SMILES were used to index the new substructures rather than the more general SMARTS because the SMARTS-matching routine was prohibitively slow with a large library. All SMILES were computed using Open Babel's native routines.

RDKit<sup>16</sup> is an open source chemoinformatics package that includes tools for generating 3D conformations of molecules from SMILES. RDKit relies on the combination of distance geometry methods with molecular mechanics force fields. It does not use a data-driven approach and has no substructure library. RDKit predictions were made by generating a single conformation, adding explicit hydrogens, and then optimizing the structure with the UFF force field.<sup>15</sup>

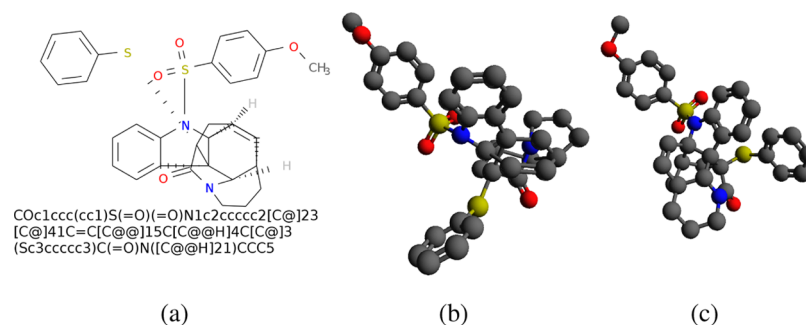
Balloon<sup>4</sup> is a freely available 3D conformer generation algorithm. Structures were predicted by generating a single conformer and performing the MMFF94 force field minimization provided with the software.<sup>17</sup>

## RESULTS

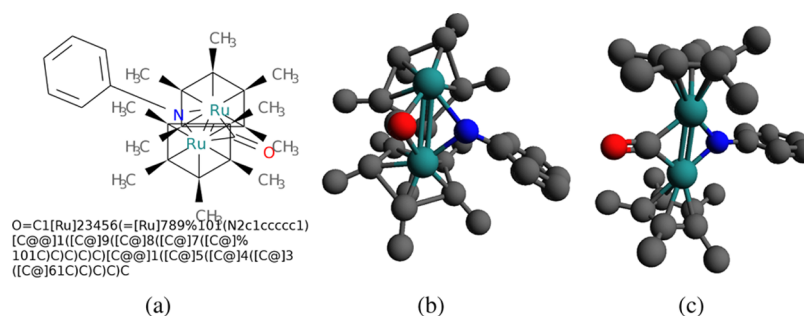
**Coverage.** Sometimes a prediction algorithm is unable to predict a good structure for a molecule and fails. In fact, none of

**Table 4. Mean RMSD (and Standard Deviation) in Å of Predicted Metal–Organic Molecule Structures for Different Structure Prediction Algorithms (rows) and Substructure Libraries (columns)**

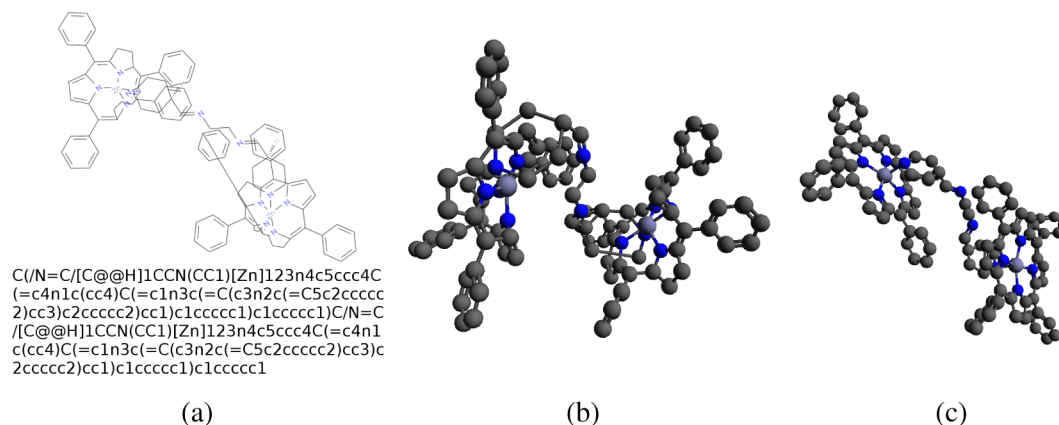
	CSD	Free	OB	none
COSMOS	1.25 (1.07)	1.68 (1.09)	—	1.97 (1.07)
Open Babel	2.10 (1.18)	2.11 (1.18)	2.11 (1.17)	2.28 (1.22)



**Figure 1.** A complex organic molecule for which COSMOS performs better than Open Babel: (a) 2D structure and isomeric SMILES, (b) 3D structure predicted by Open Babel, and (c) 3D structure predicted by COSMOS. The Open Babel and COSMOS RMSDs are 3.23 and 2.44 Å, respectively, and predictions took 1.48 and 0.21 s, respectively.



**Figure 2.** Typical metallocene complex: (a) 2D structure and isomeric SMILES, (b) 3D structure predicted by Open Babel, and (c) 3D structure predicted by COSMOS. The Open Babel and COSMOS RMSDs are 2.15 and 0.60 Å, respectively, and predictions took 2.15 and 1.21 s, respectively.



**Figure 3.** Typical large metal–organic architecture: (a) 2D structure and isomeric SMILES, (b) 3D structure predicted by Open Babel, (c) 3D structure predicted by COSMOS. The Open Babel and COSMOS RMSDs are 7.38 and 4.77 Å, respectively, and predictions took 6.66 and 0.37 s, respectively.

**Table 5. Mean Prediction Time per Molecule in Seconds (with Standard Deviation)**

COSMOS with free library	Open Babel with OB library	RDKit	Balloon
0.06 (0.16)	0.77 (0.74)	0.19 (0.28)	1.71 (3.85)

the predictors were capable of predicting every molecule in either test set. Table 2 shows that RDKit and Balloon had significant difficulty predicting complex metal–organic structures, while COSMOS had the best coverage for both the organic and metal–organic test sets.

**Accuracy.** Accuracy was measured as the RMSD of the heavy atoms. We account for differences in coverage by comparing the RMSD of the intersection set—the set of structures for which every method succeeded in predicting a structure. For the organic test set, this intersection set consists of 7154 of 9184 structures (Table 3, Figure 1); the metal–organic intersection consists of 5053 of 9595 structures (Table 4, Figure 1). RDKit and Balloon had very low coverage for the metal–organic molecules, so they were left out of the metal–organic comparison.

Surprisingly, adding substructures to the Open Babel library had little effect on accuracy. Presumably, this is because the substructures in the Open Babel library already cover a large portion of the substructures found in the test set, and the additional substructures have little impact on the final structure after force field minimization. A particular case is metallocenes, where force field minimization will give an inaccurate structure even when the initial structure is good (Figure 2). Thus, expanding the library may provide better initial structures for

these complex structures, but the force field minimization will still result in the same poor prediction.

**Speed.** COSMOS is significantly faster than the other prediction algorithms because it performs substructure matching with hash tables and uses a fast knowledge-based algorithm to optimize the final structure. Open Babel, although it uses a similar data-driven approach, is slower for two reasons: (1) It uses a SMARTS routine to match substructures with those in a library. (2) It relies on a force field minimization on the final structure (Figure 3). RDKit and Balloon also use force field minimizations. Table 5 compares the average prediction time per molecule for the common set of successfully predicted organic molecules. All experiments were carried out on an Intel Xeon 3.00 GHz processor with 48 Gb RAM.

## DISCUSSION

The COSMOS algorithm performs better than any other free prediction algorithm to our knowledge. The commonly used CORINA algorithm may offer better performance on some types of molecules, but it is commercial. CORINA is also more limited in that it is unable to make predictions on metallocene complexes and any other molecule with a bond order greater than six.

COSMOS's advantage over other structure predictors is that it makes heavy use of known molecular structures to predict new ones. It is therefore critical to have a large varied data library to make accurate predictions over different areas of chemistry. We have shown here that a library of freely available crystallography data, while a fraction of the size of the CSD, is nearly as good for predicting 3D molecular structures of both organic and metal–organic structures.

One approach we tried for expanding the substructure library even further was to predict library substructures using highly accurate but computationally expensive quantum mechanics methods. These methods are capable of modeling very complex molecular structures, both in gas phase or within a solvent,<sup>18</sup> so substructures successfully predicted in this way are accurate enough to include in our data library. However, we found that geometry optimization with these methods was very sensitive to the initial structure, and was unreliable for the rough structures we could provide as input. Thus, high-throughput quantum mechanics modeling did not seem to be a fruitful approach to expanding the substructure library.

## CONCLUSIONS

These results demonstrate that COSMOS is a versatile, fast, and accurate 3D structure predictor for drug-like molecules. Hashing substructures with isomeric SMILES keys has a significant speed advantage over Open Babel's SMARTS-matching approach, and the knowledge-based assembly algorithm is more accurate than those that rely on molecular mechanics force fields. Furthermore, the accuracy of COSMOS will improve as more crystallography data becomes available and our substructure library grows. The latest substructure library, containing almost 500,000 unique molecule fragments, is available for download with the compiled COSMOS python code. COSMOS predictions can also be made through our online server, which is part of the ChemDB chemoinformatics Web portal,<sup>19</sup> <http://cdb.ics.uci.edu>.

## AUTHOR INFORMATION

### Corresponding Author

\*E-mail: [pfbaldi@ics.uci.edu](mailto:pfbaldi@ics.uci.edu).

### Notes

The authors declare no competing financial interest.

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