# Supplementary Information for Gibbs-Helmholtz Graph Neural Network: capturing the temperature dependency of infinite dilution activity coefficients

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#### S1 Experimental techniques in the DECHEMA data collection

Percentage of datapoints in the complete DECHEMA data collection obtained by the experimental techiques: 1) Gas-liquid chromatography with gas phase correction (GLCR), 2) Gas-liquid chromatography with no gas phase correction (GLCI), 3) Gas-liquid chromatography with no specification of gas phase correction (GLCN), 4) Derived from solubility data (SOLU), 5) Dilutor technique (DILU), 6) Static method (STAT), 7) Ebulliometry (EBUL) and 8) other techniques (e.g., liquid-liquid chromatography, derived from Henry coefficients, non-steady-state gas-liquid chromatography, isopiestic technique, dew point technique, relative gas-liquid chromatography and Rayleigh distillation method) (OTHR).



Figure S1: Percentage of datapoints on the complete DECHEMA data collection obtained by different experimental techniques.

### S2 Temperature distribution on the DECHEMA dataset



Figure S2: Distribution of temperature values covered in the DECHEMA dataset.

### S3 Infinite dilution activity coefficient distribution on the DECHEMA dataset



**Figure S3:** Distribution of  $\ln \gamma_{ij}^{\infty}$  values covered in the DECHEMA dataset.

## S4 Chemical classes contained in the DECHEMA dataset

These chemical classes were obtained by the Classyfire tool [\[1\]](#page-40-0) which, to the best of our knowledge, provides the largest and most consistent taxonomy across the chemical space.

Table S1: Chemical classes contained in the DECHEMA dataset obtained from the Classyfire tool [\[1\]](#page-40-0) along the number of chemical species contained in each class.

Class	No.	Class	No.
Benzene and substituted derivatives	271	Phenanthrenes and derivatives	$\overline{4}$
Organooxygen compounds	193	Lactams	4
<b>Fatty Acyls</b>	136	Epoxides	4
Organonitrogen compounds	113	Keto acids and derivatives	3
Carboxylic acids and derivatives	104	Sulfonyls	3
Saturated hydrocarbons	103	Other non-metal organides	3
Unsaturated hydrocarbons	67	Azobenzenes	3
Prenol lipids	39	Dioxanes	3
Organofluorides	32	Homogeneous other non-metal compounds	3
Phenols	30	Pyrroles	3
Organochlorides	28	Oxanes	$\overline{2}$
Alkyl halides	27	Dioxolanes	$\overline{2}$
Pyridines and derivatives	22	Dihydrofurans	$\overline{2}$
Phenol ethers	22	Depsides and depsidones	$\overline{2}$
Naphthalenes	20	Thiophenes	$\overline{2}$
Organobromides	19	Hydroxy acids and derivatives	$\overline{2}$
Allyl-type 1,3-dipolar organic compounds	19	Organic sulfonic acids and derivatives	$\overline{2}$
Organic phosphoric acids and derivatives	12	Oxolanes	$\overline{2}$
Quinolines and derivatives	12	Organic phosphonic acids and derivatives	$\overline{2}$
Thioethers	12	Fluorenes	$\overline{2}$
Vinyl halides	12	Organic sulfuric acids and derivatives	
Thiols	11	Oxathiolanes	$\overline{2}$
Heteroaromatic compounds	11	Indoles and derivatives	2
Pyrrolidines	11	Oxathianes	$\overline{2}$
Organoiodides	10	Stilbenes	1
Halohydrins	10	Acyl halides	1
Organic oxoanionic compounds	9	Thiophenols	1
Lactones	9	Diarylheptanoids	1



#### S5 Hyperparameters for GNNprevious in the isothermal studies

The hyperparameters for GNNprevious were tuned using Optuna [\[2\]](#page-40-1) by setting the number of trials to 100 and using the corresponding ranges and scales shown in Table [S2.](#page-4-0) For hyperparameter tuning 10-fold crossvalidation was used. The final hyperparameters selected for each isothermal study are shown in Table [S3.](#page-4-1) The loss function used was Mean Squared Error (MSE).



<span id="page-4-0"></span>Table S2: Ranges used during the hyperparameter search of GNNprevious in the isothermal studies.



<span id="page-4-1"></span>

#### S6 Hyperparameters for SolvGNN in the isothermal studies

The hyperparameters for SolvGNN were tuned using Optuna [\[2\]](#page-40-1) by setting the number of trials to 100 and using the corresponding ranges and scales shown in Table [S4.](#page-5-0) For hyperparameter tuning 10-fold crossvalidation was used. The final hyperparameters selected for each isothermal study are shown in Table [S5.](#page-5-1) The loss function used was Mean Squared Error (MSE).

<span id="page-5-0"></span>

<b>Hyperparameter</b>	Range	<b>Search scale</b>
Hidden embedding size	16-256	integer
Learning rate	$0.0001 - 1$	loguniform
Epochs	100-300	integer
Batch size	4-64	integer

Table S5: Final selected hyperparameters for SolvGNN in each isothermal study.

<span id="page-5-1"></span>

# S7 Hyperparameters for GNNCat, GH-GNN, SolvGNNCat and SolvGN-NGH in the temperature dependency studies

The hyperparameters of GNNCat and SolvGNNCat were optimized using Optuna [\[2\]](#page-40-1) by setting the number of trials to 100, the number of epochs to 50 and using the corresponding ranges and scales shown in Tables [S6](#page-6-0) and [S7.](#page-6-1) The final hyperparameters selected are also shown in Tables [S6](#page-6-0) and [S7,](#page-6-1) correspondingly. For hyperparameter tuning 10-fold cross-validation was used with the ranges specified in Table . After the other hyperparameters were selected, the number of epochs were varied over the shown values to select the one that improves the performance on the validation set. The loss function used was Mean Squared Error (MSE). For direct comparison, the hyperparameters of GH-GNN and SolvGNNGH were set to the analogous models GNNCat and SolvGNNCat, respectively. Notice that since GNNCat and SolvGNNCat use only a single multi-layer perceptron (MLP) at the end to predict  $\ln \gamma_{ij}^{\infty}$  and to conserved the same number of model parameters between analogous models, the first hidden-layer of the MLP in GNNCat and SolvGNNCat was set to be twice the specified hidden embedding size. The resulting number of model parameters were: 2,483,580 for GNNCat and GH-GNN and 1,798,825 for SolvGNNCat and SolvGNNGH.

<span id="page-6-0"></span>Table S6: Ranges used during the hyperparameter search of GNNCat in the temperature dependency studies. The number of epochs was set to 50 for each trial.

Hyperparameter	Range	<b>Search scale</b>	<b>Selected value</b>
Hidden embedding size	16-256	integer	113
Learning rate	$0.0001 - 1$	loguniform	0.0002
Epochs	$\{100, 150, 200, 250, 300\}$	categorical	250
Batch size	4-64	integer	32

<span id="page-6-1"></span>Table S7: Ranges used during the hyperparameter search of SolvGNNCat in the temperature dependency studies. The number of epochs was set to 50 for each trial.



#### S8 Binary systems used for training GH-GNN

Collection of all solvent-solute chemical classes contained in the training set used for developing the GH-GNN model. According to the discussion of the results section in the paper regarding the discrete extrapolation, systems with more than 25 occurrences are expected to produce results with a MAE of approximately 0.3. This systems are marked with a star. "NA" denotes that the class for such compound is "Not-available" according to Classyfire [\[1\]](#page-40-0).

Table S8: Binary solvent-solute classes contained in the training set used for developing GH-GNN and their occurrences.













![](_page_13_Picture_304.jpeg)

![](_page_14_Picture_259.jpeg)

![](_page_15_Picture_256.jpeg)

![](_page_16_Picture_256.jpeg)

![](_page_17_Picture_257.jpeg)

![](_page_18_Picture_256.jpeg)

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![](_page_29_Picture_257.jpeg)

![](_page_30_Picture_172.jpeg)

#### S9 Percentage of systems below absolute error in isothermal studies

Table S9: Percentage of systems in the test set that can be predicted by all models below the absolute error thresholds 0.1, 0.2 and 0.3 for temperature 20◦C. RF refers to the random forest model. Higher is better, the best value per threshold is bold.

Method/AE	0.1	0.2	0.3
RF	22.35	39.41	52.35
UNIFAC (Do)	45.88	65.88	75.88
<b>COSMO-RS</b>	30.59	50.00	64.71
<b>MOSCED</b>	53.53	78.24	85.88
<b>GNNprevious</b>	31.18	56.47	70.00
SolvGNN	51.76	70.59	82.94

Table S10: Percentage of systems in the test set that can be predicted by all models below the absolute error thresholds 0.1, 0.2 and 0.3 for temperature 25◦C. RF refers to the random forest model. Higher is better, the best value per threshold is bold.

![](_page_31_Picture_84.jpeg)

Method/AE	0.1	0.2	0.3
RF	23.33	38.00	50.67
UNIFAC (Do)	32.67	53.33	68.00
COSMO-RS	24.00	46.00	60.00
<b>MOSCED</b>	54.00	76.67	84.67
GNNprevious	41.33	62.00	80.00
SolvGNN	42.00	70.67	79.33

Table S11: Percentage of systems in the test set that can be predicted by all models below the absolute error thresholds 0.1, 0.2 and 0.3 for temperature 30◦C. RF refers to the random forest model. Higher is better, the best value per threshold is bold.

Table S12: Percentage of systems in the test set that can be predicted by all models below the absolute error thresholds 0.1, 0.2 and 0.3 for temperature 40◦C. RF refers to the random forest model. Higher is better, the best value per threshold is bold.

Method/AE	01	02	03
RF	27.41	40.00	54.07
UNIFAC (Do)	27.41	52.59	65.93
COSMO-RS	21.48	41 48	62.22
<b>MOSCED</b>	45.19	66.67	72.59
GNNprevious	33.33	55.56	71 11
SolvGNN	48.89	68.15	77.78

Table S13: Percentage of systems in the test set that can be predicted by all models below the absolute error thresholds 0.1, 0.2 and 0.3 for temperature 50◦C. RF refers to the random forest model. Higher is better, the best value per threshold is bold.

![](_page_32_Picture_130.jpeg)

Method/AE	0.1	02	0.3
RF	26.47	44.85	61.03
UNIFAC (Do)	36.03	59.56	70.59
COSMO-RS	28.68	47.06	62.50
<b>MOSCED</b>	47.79	68.38	82.35
GNNprevious	34.56	72.06	82.35
SolvGNN	45.59	71.32	86.76

Table S14: Percentage of systems in the test set that can be predicted by all models below the absolute error thresholds 0.1, 0.2 and 0.3 for temperature 60◦C. RF refers to the random forest model. Higher is better, the best value per threshold is bold.

Table S15: Percentage of systems in the test set that can be predicted by all models below the absolute error thresholds 0.1, 0.2 and 0.3 for temperature 70◦C. RF refers to the random forest model. Higher is better, the best value per threshold is bold.

Method/AE	0.1	02	03
RF	23.29	45.21	53.42
UNIFAC (Do)	36.99	65.75	80.82
COSMO-RS	27.40	38.36	60.27
<b>MOSCED</b>	49.32	65.75	76.71
<b>GNNprevious</b>	50.68	72.60	79.45
SolvGNN	54.79	69.86	76 71

Table S16: Percentage of systems in the test set that can be predicted by all models below the absolute error thresholds 0.1, 0.2 and 0.3 for temperature 80◦C. RF refers to the random forest model. Higher is better, the best value per threshold is bold.

![](_page_33_Picture_143.jpeg)

Table S17: Percentage of systems in the test set that can be predicted by all models below the absolute error thresholds 0.1, 0.2 and 0.3 for temperature 100◦C. RF refers to the random forest model. Higher is better, the best value per threshold is bold.

Method/AE	0.1	0.2	0.3
RF	18.60	30.23	34.88
<b>UNIFAC</b> (Do)	32.56	60.47	83.72
COSMO-RS	16.28	48.84	62.79
<b>MOSCED</b>	39.53	53.49	74.42
GNNprevious	37.21	76.74	86.05
SolvGNN	39.53	6744	74.42

# S10 Binary systems contained in the external dataset used for discrete extrapolation testing

Collection of all solvent-solute chemical classes contained in the external dataset used for testing the GH-GNN model for discrete extrapolation. If either the solute or solvent chemical class is missing, this indicates that that the class for such compound is "Not-available" according to Classyfire [\[1\]](#page-40-0).

Table S18: Binary solvent-solute classes contained in the training set used for developing GH-GNN and their occurrences.

![](_page_35_Picture_212.jpeg)

![](_page_36_Picture_257.jpeg)

![](_page_37_Picture_256.jpeg)

![](_page_38_Picture_256.jpeg)

![](_page_39_Picture_116.jpeg)

#### References

- <span id="page-40-0"></span>[1] Yannick Djoumbou Feunang, Roman Eisner, Craig Knox, Leonid Chepelev, Janna Hastings, Gareth Owen, Eoin Fahy, Christoph Steinbeck, Shankar Subramanian, Evan Bolton, et al. Classyfire: automated chemical classification with a comprehensive, computable taxonomy. *Journal of cheminformatics*, 8(1):1–20, 2016.
- <span id="page-40-1"></span>[2] Takuya Akiba, Shotaro Sano, Toshihiko Yanase, Takeru Ohta, and Masanori Koyama. Optuna: A next-generation hyperparameter optimization framework. In *Proceedings of the 25rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2019.