

# Transfer Learning with Copulas

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# Transfer Learning, Copulas... How?

- **Motivation:** Related natural systems may have similar dependencies between their inputs.
- *Transfer Learning* methods use previously gained knowledge to improve future learning processes.
- *Copulas* describe the full dependence structure between the marginal distributions of a multivariate model.
- **Idea:** Learn a common copula model for a set of tasks.  
Let the marginals vary freely.  
Use this copula to predict new points.

# Empirical validation with real-world data

- *Source* task data,  $\mathcal{D}_s = \{(x_i^{(s)}, y_i^{(s)})\}_{i=1}^{1000}$
- *Target* task data,  $\mathcal{D}_t = \{(x_i^{(t)}, y_i^{(t)})\}_{i=1}^{10}$
- Copula  $\hat{c}$  is fitted with  $PIT(\mathcal{D}_s) \cup PIT(\mathcal{D}_t)^*$
- Estimation using:  $\hat{p}(y_t|x_t) = \hat{p}(y_t)\hat{c}(\hat{P}(x_t), \hat{P}(y_t))$
- SVM Regression is outperformed:

	Abalone Avg. Test Error
G. Copula	0.011±0.023
<b>K. Copula</b>	<b>0.007±0.001</b>
SVM <sub>t</sub>	0.015±0.004
SVM <sub>s+t</sub>	1.108±0.139

- **Semi-supervised learning** is easy with Copulas!

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\* Non-parametrically, using kernel density estimations.