Symbolize Regressions with PHAL

Fraunhofer IIS

Post-Hoc model Approximation with Logic

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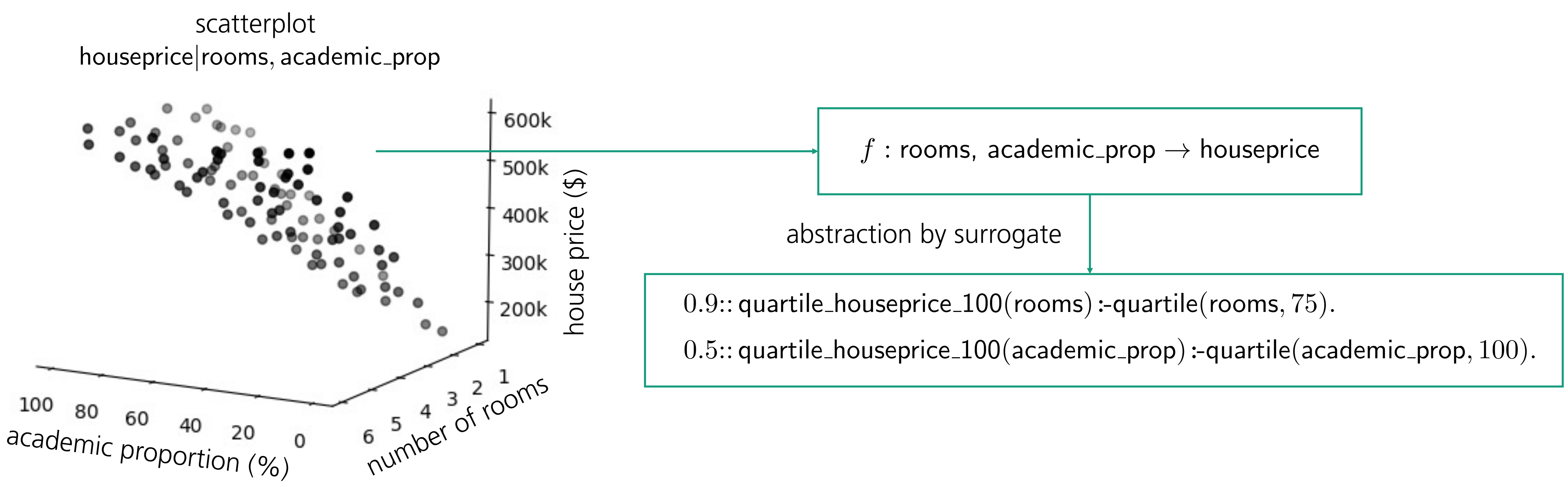
Motivation

- **Problem**: Regression models are generally built upon domain-specific expert knowledge. Their ex-post extension by domain experts with novel knowledge is often infeasible due to the models' complexity.
- **Solution**: We symbolize regression models with probabilistic logic. The resulting surrogate model actively considers user preferences.
- **Contribution**: We reduce the barriers to induce knowledge into regression models and show that our method is superior to the state of the art.

Approach

- **Goal**: Find a probabilistic logical surrogate model.
- **Abstraction step**: Reduce the level of measurement of features and regression target by user-defined statistical feature extraction procedures.
- **Rule learning step**: **1)** Convert extracted features into probabilistic logical predicates. **2)** Construct examples consisting out of abstracted features and target pairs. **3)** Apply the rule learner ProbFOIL+.



Example 1. Consider `Charlestown` (Boston) as a fictive example with an average house price of $\$750,000$ and an average of 4 rooms per house. Let us say that in `Charlestown`, the house price is caused by the room number with a probability of 90%, which can be expressed in probabilistic logic as:
0.9 :: houseprice(`Charlestown`, $\$750,000$) :- rooms(`Charlestown`, 4).

Example 2. Assume that we cannot capture whether an average of 4 rooms per house is high or low. We abstract the scalar 4 into its corresponding quartile value by: quartile(rooms(`Charlestown`)) $= 75$, which means that 75% of all districts in Boston on average have 4 or less rooms per house.

Definition 1 (Inverse Coefficient of Variation)**.** Let the *inverse coefficient of variation* (inverse cv) approximate the probability of y to be true. Then, $y_{prob} = 1 - cv$, where $cv = y_{cov} \times (y_{mean} + l)^{-1}$ with $l > 0$ and $cv = [0, 1]$.

Example 3. We set $l = 0.01$ to account for divisions by 0. We know from Ex. 1 the average house price of `Charlestown`, which is $\$750,000$. Assume for now that it origins in a GPR with $y_{cov} = \$375,000$. Inserting the numbers into the equation of Def. 1 yields: $y_{prob} = 1 - (375,000 \times (750,000 + 0.01)^{-1}) \approx 0.5$.

Example 4. Let us translate the average room number of `Charlestown`, the only entry in $\mathcal{X}_{Exp}$, into ProbLog syntax: $t(x_1^{(1)})$ = p_1_1. The feature name is retrieved by: $name(x_1)$ = rooms. Referencing Ex. 2, we straightforward formulate: quartile(p_1_1, 75). We specify the target predicate quartile_houseprice_100 and assume that it is satisfied by `Charlestown`. Recycling y_{prob} from Ex. 3 gives:
0.5 :: quartile_houseprice_100(p_1_1).

Evaluation

Table 1: Surrogate quality. We highlight Welch's tests with $p \leq 0.05$ (m^*).

Data	Method	Δ-fp	Δ-fn	# Rules	∅ Features	S
Housing	PHAL	**0.04** (0.03)	**0.11*** (0.09)	7.20 (0.84)	2.87 (0.51)	**0.85*** (0.04)
Housing	GridEx	0.09 (0.05)	0.39 (0.40)	**5.00*** (0.00)	**1.40*** (0.55)	0.19 (0.01)
Wine	PHAL	**0.04** (0.02)	**0.07** (0.04)	**2.80*** (0.84)	3.68 (0.29)	**0.87*** (0.06)
Wine	GridEx	0.09 (0.05)	0.47 (0.20)	4.40 (1.14)	**1.40*** (0.89)	0.26 (0.03)

- **Strategy**: Comparison of PHAL to GridEx for Housing and Wine data sets wrt. fidelity (Δ-fp , Δ-fn), complexity (# Rules , ∅ Features), and stability (S).
- **Results**: Whereas the surrogate's complexity does not reveal a clear trend, PHAL is superior in terms of fidelity and stability.

Outlook

- Enrich PHAL with the ability to return continuous values.
- Conduct further experiments with several feature extraction procedures.
- Apply PHAL to parameterization in the automotive sector.
- Exploit PHAL to develop explainable and interactive training procedures for regression models.

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