Cross-data Automatic Feature Engineering via Meta-learning and Reinforcement Learning

Jianyu Zhang[1], Jianye Hao[1], Francoise Fogelman-Soulié[2]

[1]College of Intelligence and Computing, Tianjin University, China
[2]Hub France IA, Paris, France

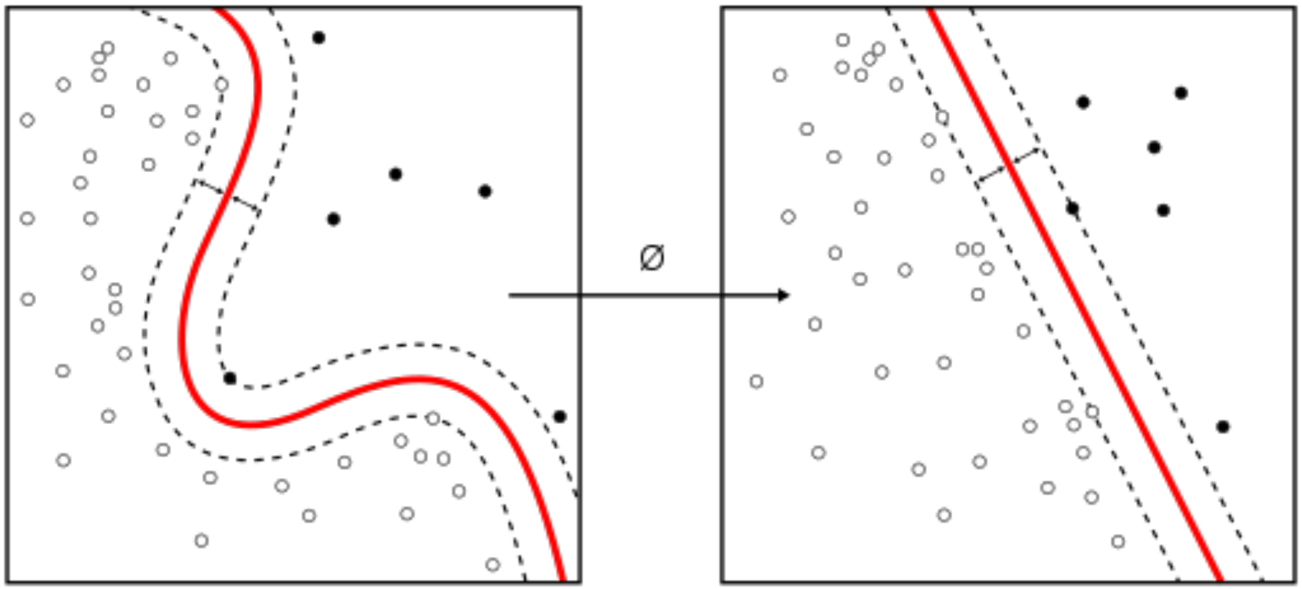
PAKDD 2020
May 13th, 2020
Online

Contents

- Problem Overview
- Related Work
- Methods
- Experiments
- Conclusion

Problem Overview

- What is Feature Engineering?
  - Create new features to help machine learning algorithm make better use of the data.



https://en.wikipedia.org/wiki/Feature_engineering

Problem Overview

- Where is the Problem of traditional Feature Engineering?
  - Requires expert knowledge
    - This is hard and time-consuming
- We propos *CAFEM*:
  - Formulate Feature Engineering by *Feature Transformation Graph* (FTG)
  - Learn to **automatically** generate features for a dataset by Reinforcement Learning (FeL).
  - Extend FeL to cross-data level by Meta-learning.

Related Work

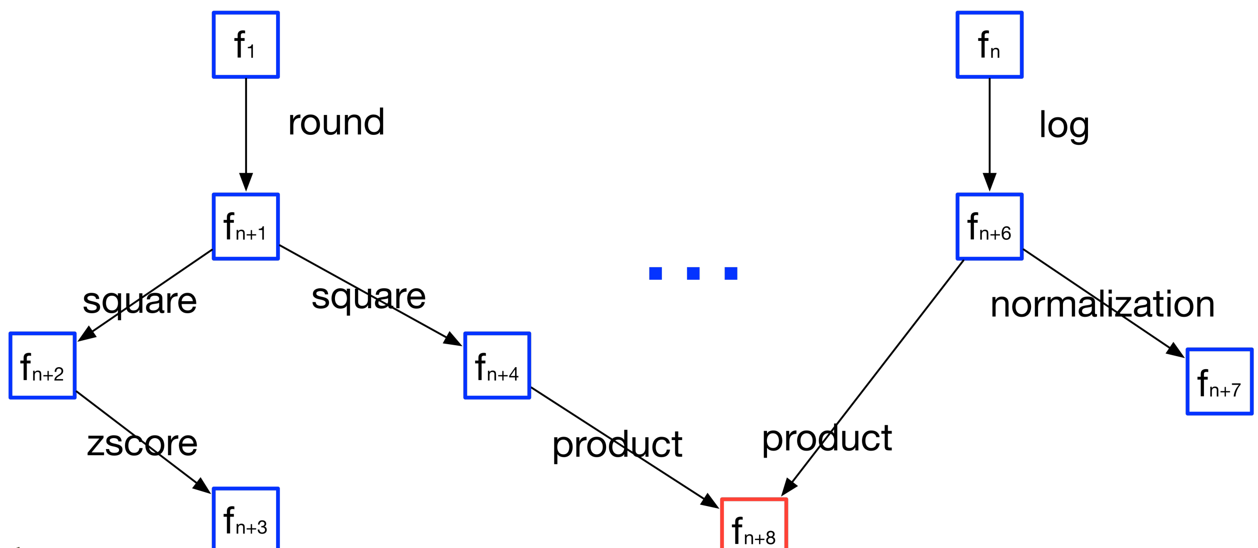
- Top-down approach
  - Generate all candidate features, then feature selection; Costly
  - Examples
    - *AFEM* (J. Zhang et al. WISE 2018), *ExploreKit* (Katz et al. ICDM 2016), Data Science Machine *DSM* (Kanter et al. DSAA 2015) and One Button Machine *OneBM* (Lam et al. arXiv 2017).
- Bottom-up approach
  - Features are progressively added and evaluated
  - Examples
    - *LFE* (Nargesian et al. IJCAI 2017), *Cognito* (Khurana et al. ICDMW 2016), *FERL* (Khurana et al. AAAI-18)

Background

- Reinforcement Learning (RL)
  - Markov Decision Process
  - States, Actions and Rewards
  - Optimal sequence of actions
- Meta-Learning
  - Quickly train a model for a new task
  - Model-Agnostic Meta-Learning (MAML)
  - Find parameters θ that is close to all tasks' optimal parameters

Methods

- Feature Transformation Graph (FTG)
  - Node: an original feature or generated feature
  - Edge: an **operator** (e.g. log, product) that transforms one/two features to a new feature
    - We defined a set of Order-1 (e.g. square) and Order-2 operators (e.g. product)



Methods

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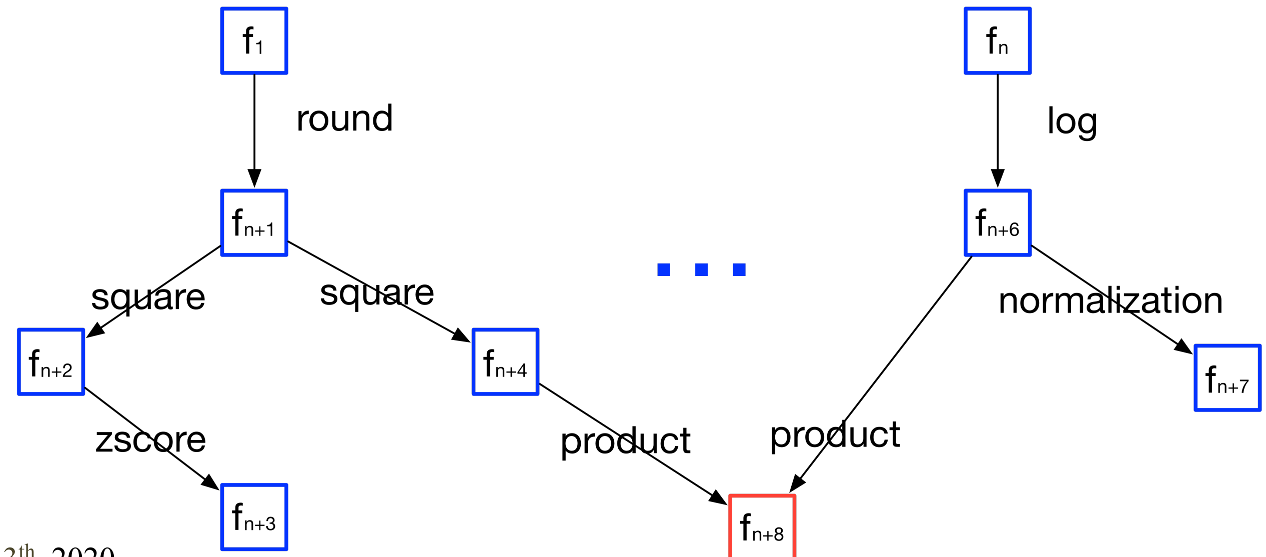


Methods

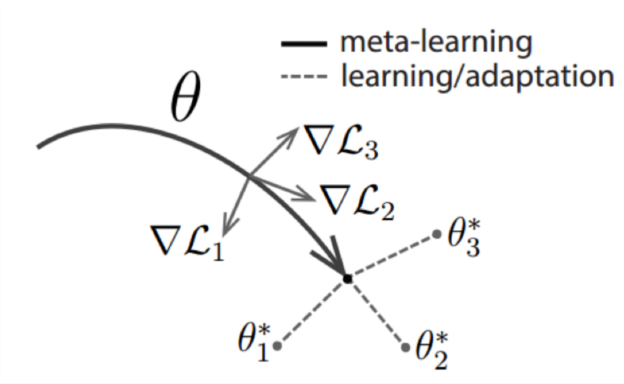
- Learn Feature Engineering by RL (FeL)
  - State:
    - Current FTG
    - We represent current FTG by a set of features
    - Such as # of each operators in FTG, node depth of a feature, average performance improvement of an action.
    - In total, we use 293 features to represent each state.
  - Action
    - Feature Generation: selects an operator and one/two features in FTG, then apply the operator on the features.
    - Feature selection: eliminates an feature from FTG.

Methods

- Reward
  - Performance improvements of classification/regression tasks (evaluation step) after applying an action.
- Budget: Total # of evaluation steps.
  - Evaluation steps is costly.
  - We train RL within the budget.

Methods

- Cross-data extension by Meta-Learning (CAFEM)
  - Speed up training by learning on a set of datasets
  - Model-Agnostic Meta-Learning
  - Find parameters θ on a set of datasets, so that it close to optimal parameters θ_i^* of all individual datasets.



https://arxiv.org/pdf/1703.03400.pdf

Experiments

- Collect 120 classification/regression datasets from OpenML https://www.openml.org
- 13 transformation operators:
  - Order-1 (Log, Round, Sigmoid, Tanh, Square, Square Root, ZScore, Min-Max- Normalization)
  - Order-2 (Sum, Difference, Product, Division)
- Baseline methods:
  - Random-FeL, Brute-force, LFE, FERL
- Evaluation metrics:
  - F1-Score / 1 - Relevant Absolute Error

Experiments

- FeL classification/regression Performance (Random forest with 5-fold CV)

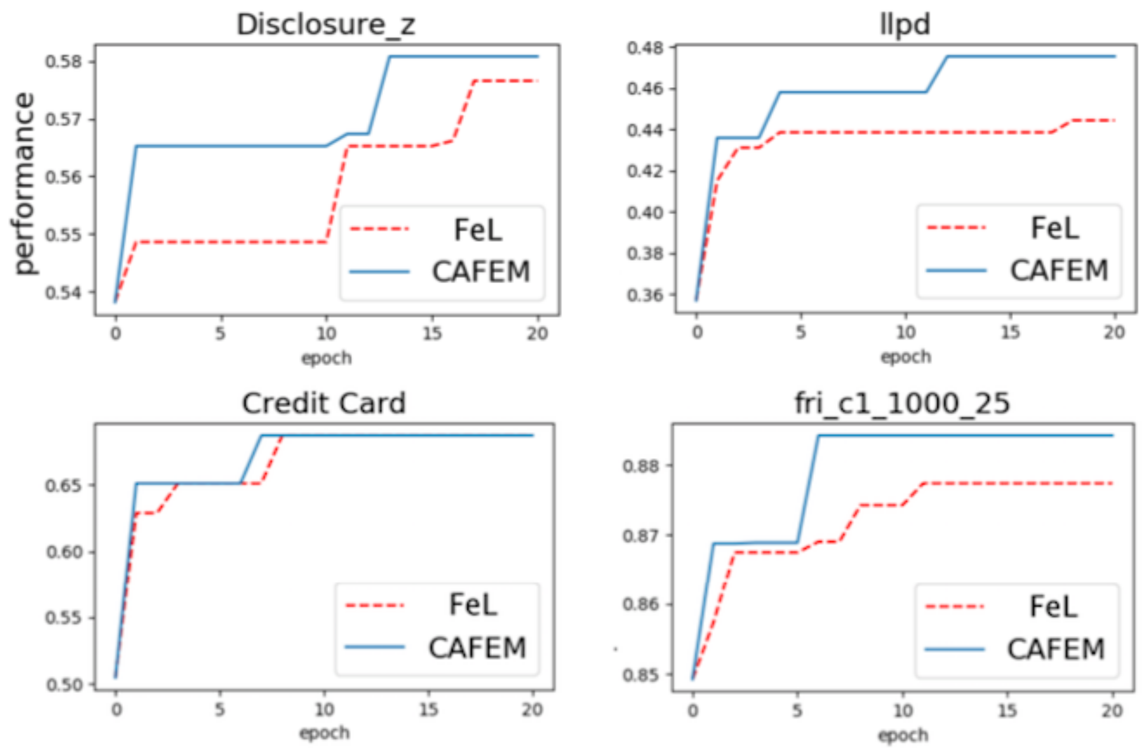
Datasets	#Row	#Feature	Baseline	Order-1					Order-1 & 2				
				FeL	BF	LFE	RS	FERL	FeL	BF	LFE	RS	FERL
Balance_scale	625	5	88.2%	88.3%	86.4%	88.2%	88.2%	**88.6%**	95.0%	**97.0%**	95.1%	92.7%	-
Boston	506	21	88.2%	**90.2%**	86.7%	89.2%	89.5%	88.7%	**89.9%**	85.6%	88.2%	89.8%	-
ClimateModel	540	21	95.5%	**96.0%**	95.6%	95.5%	95.7%	95.9%	**96.1%**	95.5%	95.5%	**96.1%**	-
Cpu_small	8,192	13	86.3%	**87.1%**	84.5%	85.8%	86.6%	86.8%	**87.1%**	86.2%	86.3%	87.0%	-
Credit card	14,240	31	50.5%	**68.7%**	64.8%	50.5%	63.8%	64.0%	**71.4%**	65.1%	65.1%	64.6%	-
Disclosure_x	662	4	44.8%	**51.7%**	46.6%	46.8%	49.7%	49.8%	51.4%	46.4%	46.4%	51.4%	**51.8%**
Disclosure_z	662	4	53.8%	**57.7%**	55.6%	53.1%	55.6%	57.0%	**57.0%**	53.8%	55.0%	56.7%	56.9%
fri_c1_1000_25	1,000	26	84.9%	87.7%	85.8%	85.8%	86.7%	**88.0%**	**87.1%**	77.9%	82.1%	**87.1%**	-
Fri_c2_100_10	1,000	11	86.3%	**89.7%**	85.8%	86.8%	88.6%	89.3%	**91.0%**	87.2%	86.7%	89.3%	-
Fri_c3_100_5	1,000	6	88.2%	89.2%	88.5%	88.2%	88.4%	**89.4%**	**90.7%**	87.3%	87.1%	89.3%	-
fri_c3_1000_50	1,000	51	79.7%	83.7%	**88.5%**	80.9%	80.7%	87.8%	83.1%	**88.4%**	78.3%	80.8%	-
Gina_agnostic	3,468	971	92.3%	92.8%	78.9%	92.3%	92.8%	**93.5%**	**92.8%**	-	92.5%	92.8%	-
Hill-valley	1,212	101	57.5%	**61.7%**	59.2%	57.5%	60.8%	61.1%	**100%**	**100%**	57.5%	99.9%	-
Ilpd	583	11	41.3%	**45.7%**	38.7%	38.9%	43.6%	44.9%	**45.9%**	**45.9%**	42.4%	44.8%	-
Kc1	2,109	22	40.4%	**44.5%**	35.3%	38.9%	42.0%	42.7%	**44.4%**	39.9%	38.8%	43.4%	-
openml_589	1,000	25	66.9%	67.7%	55.0%	X	67.2%	**72.6%**	75.0%	**76.9%**	X	68.1%	-
Pc4	1,458	38	47.7%	57.0%	36.2%	45.3%	53.8%	**58.4%**	**58.1%**	50.1%	55.1%	56.5%	-
Pc3+C14	1,563	38	25.9%	**33.4%**	27.9%	23.0%	30.3%	32.0%	**33.3%**	24.6%	27.4%	31.6%	-
Spectrometer	531	103	77.3%	**83.9%**	80.0%	75.2%	80.4%	83.0%	82.7%	**90.8%**	73.2%	81.8%	-
Strikes	625	7	96.6%	**99.5%**	98.7%	97.8%	99.1%	98.9%	**99.5%**	97.8%	93.4%	99.4%	98.9%

Experiments

- Robustness of FeL on learning algorithms
  - Random Forest: 4.2% improvement
  - Logistic Regression: 10.8% improvement

Experiments

- Cross-data Extension (CAFEM) Performance
  - Training on 100 datasets
  - Few shots learning on other 20 datasets.



Conclusion

- Feature engineering influences performances a lot but it is the most time-consuming part of data mining.
- We propose Feature Transformation Graph (FTG) to organize the feature engineering (FE) process and FE learner (FeL) to learn FE by Reinforcement Learning.
- We extend FeL to cross-data level (CAFEM) by meta-learning.
- Our framework out performs state-of-the-art methods.

Thanks for your attention

Q & A