Automated Machine Learning (AutoML) in Insurance

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1. Introduction to AutoML

Machine learning (ML) is a field of **Artificial Intelligence (AI)** and “a field of inquiry devoted to understanding and building methods that 'learn', that is, methods that **leverage data** to improve performance on some set of tasks”. [1]

Common application scenarios:

(1) Self Driving Cars
(2) Recommending Systems
(3) Automated Translation
(4) ….

Fig. Self-Driving Cars [2]

For Insurance:

(1) Predict future claim frequency/severity
(2) Fraud prevention
(3) …

[1] Mitchell, T. M., & Mitchell, T. M. (1997). *Machine learning* (Vol. 1, No. 9). New York: McGraw-hill.
[2] https://www.imeche.org/news/news-article/webinar-autonomous-vehicles---the-challenges-of-automated-driving

1. Introduction to AutoML

However, ML tasks can be **experience-dependent** and **heavy manual work**.

Given the nature of ML algorithms, which are **data-driven**, selection of models and hyperparameters are critical for each dataset, and **no universal solution** exists.

Furthermore, industrial datasets usually are not well-formatted or well-organized, and problems like **missing values**, **irrelevant features**, **imbalance distributions** exists.

It's difficult for those who have no previous experience/knowledge to gain hands-on experience.

1. Introduction to AutoML

Automated Machine Learning (AutoML) is one of the solutions.

AutoML tries to automatically select a ML model and tuning for optimal hyperparameters, so that "non-expert users" can apply ML to their application scenarios more effectively and "achieve improved performance". [3]

AutoML is an active research topic, where problems like efficiency, search algorithms are all in development.

[3] Thornton, C., Hutter, F., Hoos, H. H., & Leyton-Brown, K. (2013, August). Auto-WEKA: Combined selection and hyperparameter optimization of classification algorithms. In *Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining* (pp. 847-855).

1. Introduction to AutoML

Key criteria of AutoML:

(1) **Better Performance**
What's a proper search space; How the model/hyperparameter evaluated;
Better model search algorithms, hyperparameter optimization algorithms; …

(2) **Higher Efficiency**
AutoML usually evaluate by training multiple models, how to more efficiently assess
(or sometimes with limited computation resources)

(3) **Ease of use, Robustness**
The goal is to ease expertise required, a robust AutoML for all possible scenarios

1. Introduction to AutoML

Our AutoML pipeline:

(1) Complete, fully functional processing and model tuning

(2) Special treatment for imbalanced datasets

(3) Record training process and store the optimal pipeline for continued applications

2. Components & Pipline

1. Data Encoding
2. Data Imputation
3. Data Balancing
4. Data Scaling
5. Feature Selection
6. Classification/Regression Models
7. Model Selection and Hyperparameter Optimization

Preprocessing

2. Components & Pipeline

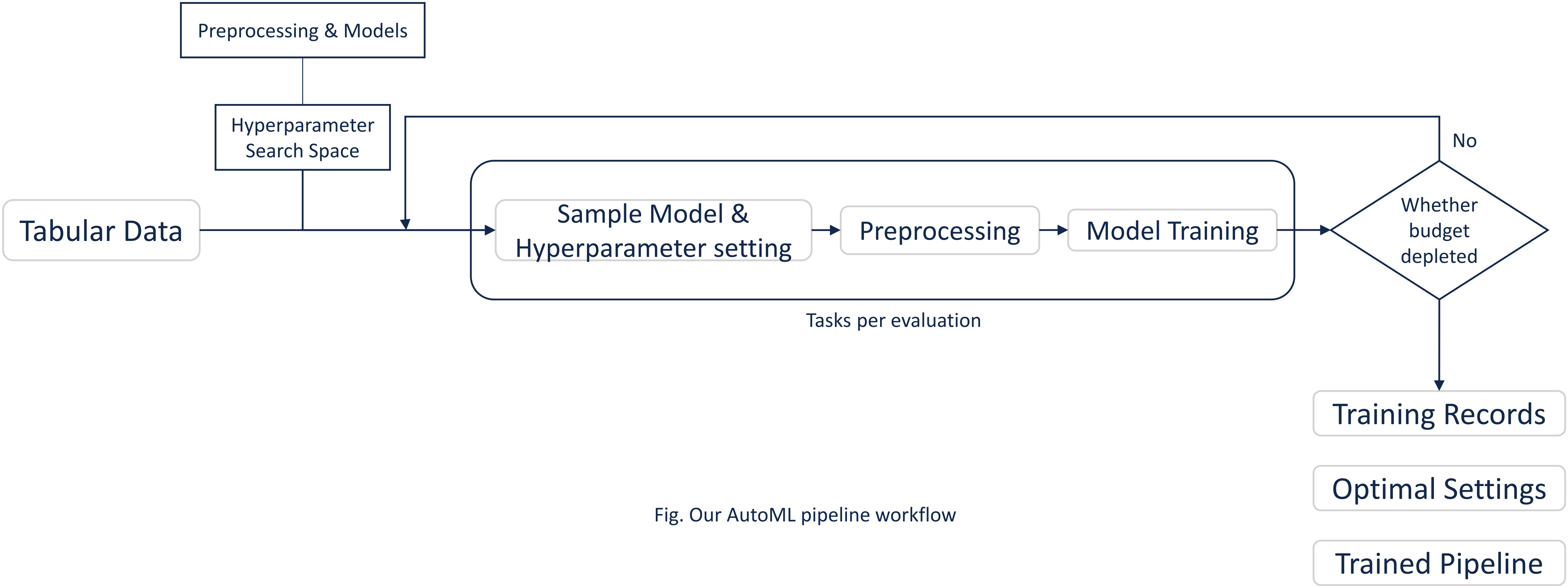


Fig. Our AutoML pipeline workflow

2.1. Data Encoding

Real-life datasets sometimes contain features of **string type**.

age	sex	bmi	children	smoker	region	expenses
19	female	27.9	0	yes	southwest	16884.92
18	male	33.8	1	no	southeast	1725.55
28	male	33	3	no	southeast	4449.46
33	male	22.7	0	no	northwest	21984.47
32	male	28.9	0	no	northwest	3866.86
31	female	25.7	0	no	southeast	3756.62
46	female	33.4	1	no	southeast	8240.59
37	female	27.7	3	no	northwest	7281.51
37	male	29.8	2	no	northeast	6406.41

Convert unique strings to numerical types

age	sex	bmi	children	smoker	region	expenses
19	0	27.9	0	1	3	16884.92
18	1	33.8	1	0	2	1725.55
28	1	33	3	0	2	4449.46
33	1	22.7	0	0	1	21984.47
32	1	28.9	0	0	1	3866.86
31	0	25.7	0	0	2	3756.62
46	0	33.4	1	0	2	8240.59
37	0	27.7	3	0	1	7281.51
37	1	29.8	2	0	0	6406.41

One-hot encoding

age	bmi	children	expenses	sex_female	sex_male	smoker_no	smoker_yes	region_northeast	region_northwest	region_southeast	region_southwest
19	27.9	0	16884.92	1	0	0	1	0	0	0	1
18	33.8	1	1725.55	0	1	1	0	0	0	1	0
28	33	3	4449.46	0	1	1	0	0	0	1	0
33	22.7	0	21984.47	0	1	1	0	0	1	0	0
32	28.9	0	3866.86	0	1	1	0	0	1	0	0
31	25.7	0	3756.62	1	0	1	0	0	0	1	0
46	33.4	1	8240.59	1	0	1	0	0	0	1	0
37	27.7	3	7281.51	1	0	1	0	0	1	0	0
37	29.8	2	6406.41	0	1	1	0	1	0	0	0

Majority of common ML methods in Python does not support string as inputs, encoding becomes necessary.

2.2. Data Imputation

Some of datasets contains **missing values** where true values can not be traced.

Causes: Incomplete data entry, Save malfunction, …

Common solutions:

(1) Delete missing values.

Advantage: all remaining values are true values.

Drawback: not feasible when data size is small.

(2) Impute the missing values with estimated values.

Advantage: best utilize all available information.

Drawback: imputed values may not accurately describe the missing values, time-consuming, …

2.3. Data Balancing

Some of datasets exhibits **imbalanced nature** where majority values are the same
(e.g., 99% of policyholders do not report claims).

Traditional ML models evaluated by classical metrics may not be the ideal solution by the business perspective.

Common solutions:

(1) Increase the weights of minority class.
(2) Over-sampling on minority class/Down-sampling on majority class. [12]
(3) Create a model ensemble (multiple models weighted on prediction).
(4) Special loss metrics for gradient-based models.
(5) …

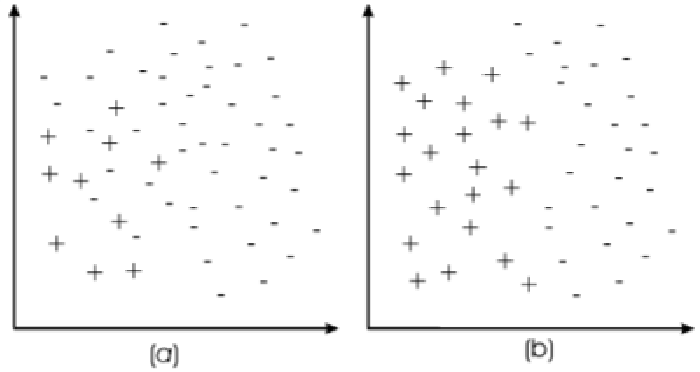


Fig. Spatial illustration of unbalanced datasets (a) and balanced datasets (b). [12]

[12] Batista, G. E., Prati, R. C., & Monard, M. C. (2004). A study of the behavior of several methods for balancing machine learning training data. *ACM SIGKDD explorations newsletter*, *6*(1), 20-29.

2.4. Data Scaling

Scaling intends to transform data to fit specific scale so it may converge more easily. Incorporated Scaling methods:

2.4.1. Standardize

2.4.2. Normalize

2.4.3. Robust Scaling

2.4.4. Min-Max Scaling

2.4.5. Power Transformer

2.4.6. Winsorization

2.5. Feature Selection

Modern datasets have hundreds of (or even more) features with exploding size.

However, some of them may be reductant or irrelevant, which may decrease the model performance while still takes long training time. One of the solution is using **feature selection** to select only subset of features for model training.

Common categories of feature selection [20]:

1. **Filter:** use statistical analysis in only feature space
2. **Wrapper:** train a model on feature subsets and use performance as selection criteria.
3. **Embedded:** embed feature importance into model training and use as selection criteria.
4. **Hybrid:** combine filter and wrapper for feature selection.

[20] Chandrashekar, G., & Sahin, F. (2014). A survey on feature selection methods. *Computers & Electrical Engineering*, *40*(1), 16-28.

2.6.1. Classification Models

Incorporated Classification models:

2.6.1.1. Linear Models
Logistic Regression, Stochastic Gradient Descent,
Generalized Additive Models (GAM) [38]

2.6.1.2. Tree Models
Decision Tree, Extra Trees, Random Forest, Adaboost [28],
Hist Gradient Boosting, Light Gradient Boosting Machine (LightGBM) [36],
Extreme Gradient Boosting (XGBoost) [37]

2.6.1.3. Nearest Neighbors
K Nearest Neighbors

2.6.1.4. Support Vector Machine
Linear SVM [30], Kernel SVM [31]

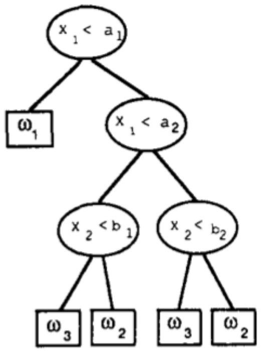


Fig. Decision Tree Split [29]

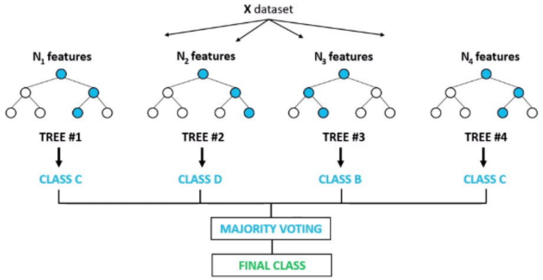


Fig. Random Forest [41]

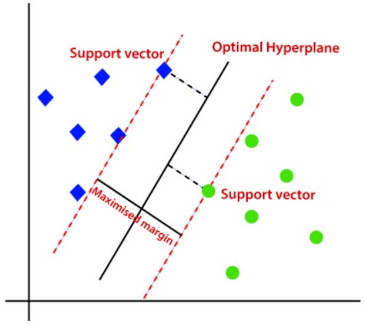


Fig. Support Vector Machine [32]

[28] Hastie, T., Rosset, S., Zhu, J. & Zou, H. Multi-class adaboost. *Statistics and its Interface* **2**, 349–360 (2009).
[29] Safavian, S. R. & Landgrebe, D. A survey of decision tree classifier methodology. *IEEE transactions on systems, man, and cybernetics* **21**, 660–674 (1991).
[30] Fan, R.-E., Chang, K.-W., Hsieh, C.-J., Wang, X.-R. & Lin, C.-J. Liblinear: A library for large linear classification. *the Journal of machine Learning research* **9**, 1871–1874 (2008).
[31] Chang, C.-C. & Lin, C.-J. Libsvm: a library for support vector machines. *ACM transactions on intelligent systems and technology (TIST)* **2**, 1–27 (2011).
[32] https://medium.com/@viveksalunkhe80/support-vector-machine-svm-88f360ff5f38
[36] Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., ... & Liu, T. Y. (2017). Lightgbm: A highly efficient gradient boosting decision tree. *Advances in neural information processing systems*, *30*.
[37] Chen, T., & Guestrin, C. (2016, August). Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining* (pp. 785-794).
[38] Servén D., Brummitt C. (2018). pyGAM: Generalized Additive Models in Python. Zenodo. DOI: 10.5281/zenodo.1208723
[41] https://www.freecodecamp.org/news/how-to-use-the-tree-based-algorithm-for-machine-learning/

2.6.1. Classification Models

Incorporated Classification models:

2.6.1.5. Naïve Bayes (NB)

Bernoulli NB, Gaussian NB, Multinomial NB

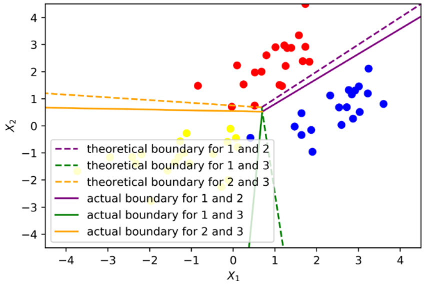
2.6.1.6. Discriminant Analysis

Linear Discriminant Analysis (LDA),
Quadratic Discriminant Analysis (QDA)

2.6.1.7. Others

Multi-Layer Perception (MLP),
Passive Aggressive (PA)

Fig. Illustration of LDA



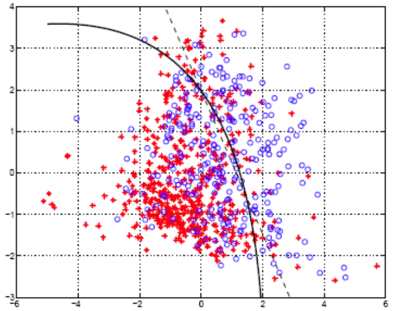
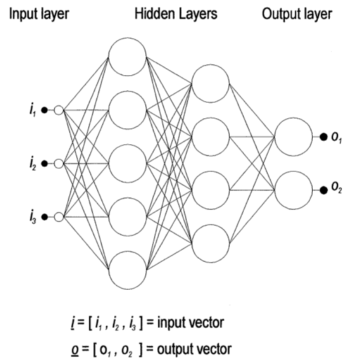


Fig. Illustration of QDA[42]

Fig. Multi-Layer Perceptron [33]



[33] Gardner, M. W. & Dorling, S. Artificial neural networks (the multilayer perceptron)—a review of applications in the atmospheric sciences. *Atmospheric environment* **32**, 2627–2636 (1998).
[42] https://online.stat.psu.edu/stat508/book/export/html/696

2.6.2. Regression Models

Incorporated Regression models:

2.6.2.1. **Linear Models**
Linear Regression, Lasso Regression, Ridge Regression,
ElasticNet, Bayesian Ridge Regression [34], Adaboost,
ARD Regression, SGD, Generalized Additive Models (GAM) [38]

2.6.2.2. **Tree Models**
Decision Tree, Extra Trees, Random Forest,
Hist Gradient Boosting,
Light Gradient Boosting Machine (LightGBM) [36],
Extreme Gradient Boosting (XGBoost) [37]

2.6.1.3. **Support Vector Machine**
Linear SVM [30], Kernel SVM [31]

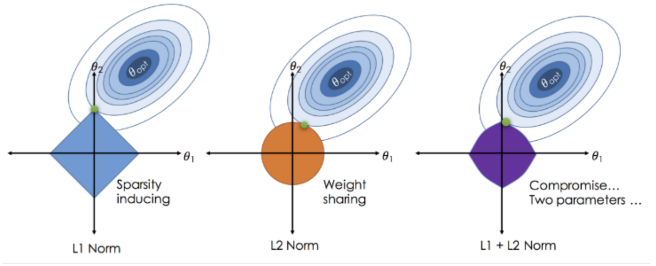


Fig. ElasticNet [43]

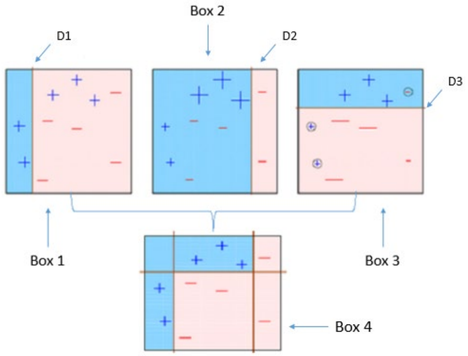


Fig. Adaboost [44]

[30] Fan, R.-E., Chang, K.-W., Hsieh, C.-J., Wang, X.-R. & Lin, C.-J. Liblinear: A library for large linear classification. *the Journal of machine Learning research* **9**, 1871–1874 (2008).
[31] Chang, C.-C. & Lin, C.-J. Libsvm: a library for support vector machines. *ACM transactions on intelligent systems and technology (TIST)* **2**, 1–27 (2011).
[36] Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., ... & Liu, T. Y. (2017). Lightgbm: A highly efficient gradient boosting decision tree. *Advances in neural information processing systems*, *30*.
[37] Chen, T., & Guestrin, C. (2016, August). Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining* (pp. 785-794).
[38] Servén D., Brummitt C. (2018). pyGAM: Generalized Additive Models in Python. Zenodo. DOI: 10.5281/zenodo.1208723
[41] https://www.freecodecamp.org/news/how-to-use-the-tree-based-algorithm-for-machine-learning/
[43] https://towardsdatascience.com/from-linear-regression-to-ridge-regression-the-lasso-and-the-elastic-net-4eaecaf5f7e6
[44] https://towardsdatascience.com/understanding-adaboost-2f94f22d5bfe

2.6.2. Regression Models

Incorporated Regression models:

2.6.2.4. **Nearest Neighbors**
K Nearest Neighbors

2.6.2.5. **Others**
Gaussian Process [35],
Multi-Layer Perception (MLP)

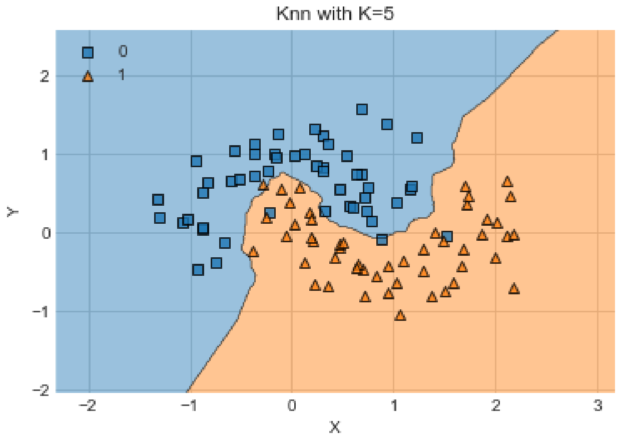


Fig. kNN [45]

[35] Wang, J. An intuitive tutorial to gaussian processes regression. *arXiv preprint arXiv:2009.10862* (2020).
[45] https://towardsdatascience.com/knn-visualization-in-just-13-lines-of-code-32820d72c6b6

2.7. Model Selection & Hyperparameter Optimization

To connect all preprocessing methods and models with hyperparameter space, we use **ray.tune** [47] for model selection and hyperparameter optimization.

ray.tune is a scalable Python package to conduct experiments on hyperparameter tuning with all common ML model structures (**scikit-learn** [39], **TensorFlow** [48], **PyTorch** [49], …) with search algorithms like **Optuna** [50], **HyperOpt** [51], …

[39] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... & Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. the Journal of machine Learning research, 12, 2825-2830.

[47] Liaw, R., Liang, E., Nishihara, R., Moritz, P., Gonzalez, J. E., & Stoica, I. (2018). Tune: A research platform for distributed model selection and training. *arXiv preprint arXiv:1807.05118*.

[48] Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., ... & Zheng, X. (2016). {TensorFlow}: a system for {Large-Scale} machine learning. In *12th USENIX symposium on operating systems design and implementation (OSDI 16)* (pp. 265-283).

[49] Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., ... & Chintala, S. (2019). Pytorch: An imperative style, high-performance deep learning library. *Advances in neural information processing systems, 32*.

[50] Akiba, T., Sano, S., Yanase, T., Ohta, T., & Koyama, M. (2019, July). Optuna: A next-generation hyperparameter optimization framework. In *Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining* (pp. 2623-2631).

[51] Bergstra, J., Yamins, D., & Cox, D. D. (2013, June). Hyperopt: A python library for optimizing the hyperparameters of machine learning algorithms. In *Proceedings of the 12th Python in science conference* (Vol. 13, p. 20).

2.7. Model Selection & Hyperparameter Optimization

```
== Status ==
Current time: 2022-07-31 15:43:49 (running for 00:03:03.19)
Memory usage on this node: 3.4/11.6 GiB
Using FIFO scheduling algorithm.
Resources requested: 0/8 CPUs, 0/0 GPUs, 0.0/5.36 GiB heap, 0.0/2.68 GiB objects (0.0/1.0 accelerator_type:G)
Current best trial: 56ae251f with loss=-0.8632478632478633 and parameters={'task_type': 'tabular_classification'}
Result logdir: /home/panyi/Git Repo/My_AutoML/tmp/heart_model
Number of trials: 64/64 (64 TERMINATED)
+---------------------------+------------+--------------------+--------------------------+--------+------------------+---------------------------------+-------------------+-----------+
| Trial name                | status     | loc                | task_type                |   iter |   total time (s) | fitted_model                    | training_status   |      loss |
|---------------------------+------------+--------------------+--------------------------+--------+------------------+---------------------------------+-------------------+-----------|
| TabularObjective_0e04be71 | TERMINATED | 192.168.1.89:13207 | tabular_classification |      4 |          1.97825 | LibSVM_SVC                      | fitted            | -0.598291 |
| TabularObjective_0f981641 | TERMINATED | 192.168.1.89:13253 | tabular_classification |      4 |          3.27871 | GaussianNB                      | fitted            | -0.769231 |
| TabularObjective_0fa7b272 | TERMINATED | 192.168.1.89:13255 | tabular_classification |      4 |         20.4705  | AdaboostClassifier              | fitted            | -0.837607 |
| TabularObjective_0fc002e1 | TERMINATED | 192.168.1.89:13259 | tabular_classification |      4 |          2.32355 | QDA                             | fitted            | -0.760684 |
| TabularObjective_0fdaf193 | TERMINATED | 192.168.1.89:13262 | tabular_classification |      4 |          3.57492 | BernoulliNB                     | fitted            | -0.589744 |
| TabularObjective_0feb97b1 | TERMINATED | 192.168.1.89:13264 | tabular_classification |      4 |        144.201   | LibSVM_SVC                      | fitted            | -0.435897 |
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| TabularObjective_1035621f | TERMINATED | 192.168.1.89:13284 | tabular_classification |      4 |          1.58028 | QDA                             | fitted            | -0.623932 |
| TabularObjective_105bf1b1 | TERMINATED | 192.168.1.89:13207 | tabular_classification |      4 |          2.67778 | LDA                             | fitted            | -0.846154 |
| TabularObjective_10f02794 | TERMINATED | 192.168.1.89:13207 | tabular_classification |      4 |          8.94002 | RandomForest                    | fitted            | -0.57265  |
| TabularObjective_13e17e33 | TERMINATED | 192.168.1.89:13284 | tabular_classification |      4 |        162.87    | GradientBoostingClassifier      | fitted            | -0.632479 |
| TabularObjective_1422f777 | TERMINATED | 192.168.1.89:13259 | tabular_classification |      4 |         12.2744  | ExtraTreesClassifier            | fitted            | -0.786325 |
| TabularObjective_144eddbc | TERMINATED | 192.168.1.89:13253 | tabular_classification |      4 |          9.62179 | MLPClassifier                   | fitted            | -0.769231 |
| TabularObjective_14c831ff | TERMINATED | 192.168.1.89:13262 | tabular_classification |      4 |          6.38417 | MultinomialNB                   | fitted            | -0.777778 |
| TabularObjective_1513c554 | TERMINATED | 192.168.1.89:13262 | tabular_classification |      4 |          3.80287 | MLPClassifier                   | fitted            | -0.794872 |
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| TabularObjective_1b71772e | TERMINATED | 192.168.1.89:13259 | tabular_classification |      4 |          4.5688  | LogisticRegression              | fitted            | -0.846154 |
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| TabularObjective_1eb61ad9 | TERMINATED | 192.168.1.89:13259 | tabular_classification |      4 |          2.27325 | LDA                             | fitted            | -0.794872 |
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| TabularObjective_232c3cae | TERMINATED | 192.168.1.89:13255 | tabular_classification |      4 |         84.4309  | KNearestNeighborsClassifier     | fitted            | -0.649573 |
| TabularObjective_2372f615 | TERMINATED | 192.168.1.89:13266 | tabular_classification |      4 |          2.80615 | LogisticRegression              | fitted            | -0.811966 |
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| TabularObjective_26030ca9 | TERMINATED | 192.168.1.89:13262 | tabular_classification |      4 |          8.97118 | AdaboostClassifier              | fitted            | -0.777778 |
| TabularObjective_274d7be4 | TERMINATED | 192.168.1.89:13259 | tabular_classification |      4 |          1.81201 | HistGradientBoostingClassifier  | fitted            | -0.846154 |
| TabularObjective_29442fec | TERMINATED | 192.168.1.89:13259 | tabular_classification |      4 |          4.62255 | BernoulliNB                     | fitted            | -0.717949 |
| TabularObjective_2a736e7a | TERMINATED | 192.168.1.89:13262 | tabular_classification |      4 |          2.88022 | LibSVM_SVC                      | fitted            | -0.632479 |
| TabularObjective_2cbd7ab9 | TERMINATED | 192.168.1.89:13259 | tabular_classification |      4 |          2.93541 | LogisticRegression              | fitted            | -0.846154 |
| TabularObjective_2d461883 | TERMINATED | 192.168.1.89:13262 | tabular_classification |      4 |         11.6529  | RandomForest                    | fitted            | -0.846154 |
| TabularObjective_2e985b00 | TERMINATED | 192.168.1.89:13259 | tabular_classification |      4 |          3.7879  | GradientBoostingClassifier      | fitted            | -0.735043 |
| TabularObjective_2f669952 | TERMINATED | 192.168.1.89:13259 | tabular_classification |      4 |         60.0609  | QDA                             | fitted            | -0.794872 |
| TabularObjective_31b73aac | TERMINATED | 192.168.1.89:13262 | tabular_classification |      4 |          5.8072  | LogisticRegression              | fitted            | -0.777778 |
| TabularObjective_35c6ead9 | TERMINATED | 192.168.1.89:13262 | tabular_classification |      4 |          1.53908 | SGD                             | fitted            | -0.837607 |
| TabularObjective_39432256 | TERMINATED | 192.168.1.89:13262 | tabular_classification |      4 |          2.51557 | PassiveAggressive               | fitted            | -0.709402 |
```

Fig. Report training process

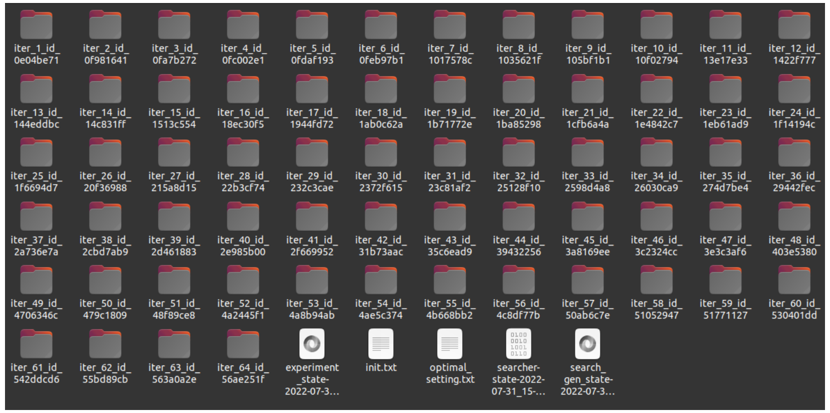


Fig. Store evaluation experiments

2.7. Model Selection & Hyperparameter Optimization

```
For pipeline 1:
Optimal encoding method is: DataEncoding
Optimal encoding hyperparameters:{}

Optimal imputation method is: no_processing
Optimal imputation hyperparameters:{}

Optimal balancing method is: EditedNearestNeighbor
Optimal balancing hyperparameters:{'imbalance_threshold': 0.9941343235473185, 'k': 1}

Optimal scaling method is: MinMaxScale
Optimal scaling hyperparameters:{}

Optimal feature selection method is: no_processing
Optimal feature selection hyperparameters:{}

Optimal classification model is: RandomForest
Optimal classification hyperparameters:{'bootstrap': True, 'criterion': 'entropy', 'max_depth': None, 'max_features': 0.5700333538264852,
'max_leaf_nodes': None, 'min_impurity_decrease': 0.0, 'min_samples_leaf': 19, 'min_samples_split': 18, 'min_weight_fraction_leaf': 0.0}
```

Fig. Record optimal setting for checking

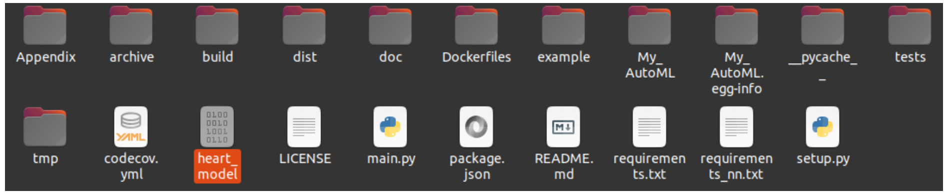


Fig. Store trained pipelines

2.7.1. Model Ensemble

To fight with data imbalance, model ensemble is another common solution, which is included in the pipeline.

Three commonly-used model ensembles are included:

1. **Stacking**
   Models are trained parallelly on all train sets, but predictions are weighted as final prediction.

2. **Bagging**
   Models are trained on subsets of train sets, and weighted predictions as final prediction.

3. **Boosting**
   Models are trained on error of past models, and all predictions summed as final prediction.

3. Live Experiments

3.1. Heart Failure Prediction (Classification)

(1) One-line command job

(2) Package-style usage

4. Summary & Future

Summary:

(1) Provide a **workable** pipeline/framework for AutoML tasks.

(2) **Performance** and **efficiency** of the pipeline for small datasets are at acceptable level.

(3) For further improvement on accuracy, **increase the time budget** to allow more search & evaluations; or use current results as **baseline** to limit further search space.

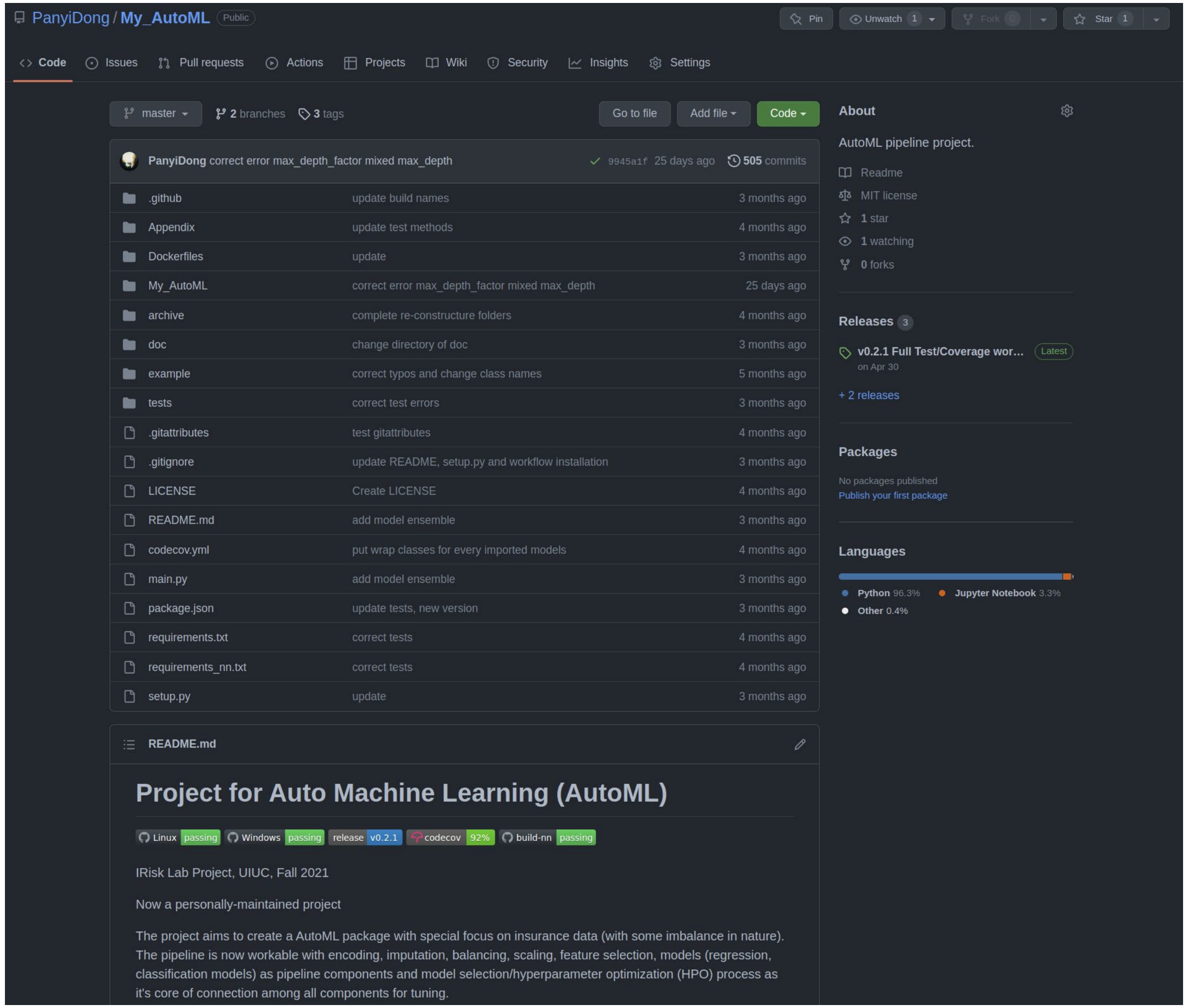
Future:

(1) Modify the search space to allow faster training; Develop/Apply better search algorithm;

(2) Find an applicable Neural Architecture Search (NAS) algorithm and hyperparameter optimization algorithm to expand allowed tasks.

(3) AutoML usually is time-consuming, computational-expansive, thus, train on large datasets are not feasible, which limits its applications. Apply Few-shot, One-shot idea to improve efficiency.

All code files, report and presentations are available at: https://github.com/PanyiDong/My_AutoML.git



Tutorials on installment, usage are all available at the page.

Thanks!

Questions