AutoML challenge winners

Victor Kocheganov

March 21, 2016

The most frequent prize-winners

djajetic (Damir Jajetic (Croatia))

4 out of 8 prizes: Final2 (2nd), AutoML3 (only one), Final3 (2nd), AutoML4 (2nd)

aad_freiburg Frank Hutter and collaborators (Freiburg, Germany)

7 out of 8 prizes: Final0 (3rd), AutoML1 (1st), Final1 (1st), AutoML2 (2nd), Final2 (3rd), Final3 (1st), AutoML4 (1st)

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ideal.intel.analytics

4 out of 4 code-free prizes: Final0 (1st), Final1 (2nd), Final2 (2nd), Final3 (3rd)

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4 out of 4 code-free prizes: Final0 (1st), Final1 (2nd), Final2 (2nd), Final3 (3rd)

djajetic approach

Simple cross validation through models

linear_model.LogisticRegression
naive_bayes.GaussianNB
f16.RandomForestClassifier
ensemble.GradientBoostingClassifier
f16.ExtraTreesClassifier
ensemble.AdaBoostClassifier
ensemble.AdaBoostClassifier (base_estimator=f16.RF)
neighbors.KNeighborsClassifier

djajetic approach

```
models = [
        {"model": 'linear_model.LogisticRegression(random_state=1)',
        "blend_group":   "LC",
            "getter":   "Lestimators = model_last.get_params()['penalty']",
            "updater":   "tries_left = 0",
             "setter":   "return in updater will end process",
             "generator":  "penalty='l2', dual=False, C=1.0 @@ " \
                            "penalty='l1', dual=False, C=1.0 @@ " \
                            "penalty='l2', dual=False, C=2.0 @@ " \
                            "penalty='l2', dual=False, C=0.5 @@ " \
                            "penalty='l2', dual=True, C=1.0 @@ " \
                            "penalty='l2', dual=True, C=0.5 @@ " \
                            "penalty='l2', dual=False, C=4.0 @@ " \
                            "penalty='l2', dual=False, C=8.0 @@ "
                            "penalty='l2', dual=False, C=1.0 @@ " \
                            "penalty='l1', dual=False, C=1.0 @@ " \
                            "penalty='l2', dual=False, C=2.0 @@ " \
                            "penalty='l2', dual=False, C=0.5 @@ " \
                            "penalty='l2', dual=True, C=1.0 @@ " \
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                            "penalty='l2', dual=False, C=4.0 @@ " \
                            "penalty='l2', dual=False, C=8.0 @@ "
        },
        {"model": 'naive_bayes.GaussianNB()',
        "blend_group":   "NB",
            "getter":   "Lestimators = model_last.get_params()",
            "updater":   "tries_left = 0",
             "setter":   "",
             "generator":  ""
        },
```
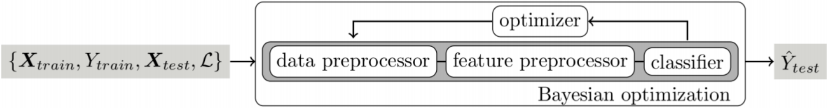

aad_freiburg approach

State-of-the-art before this guy (Auto-WEKA):



Data preprocessing

Algorithms that change data values

1. Rescaling of inputs
2. Imputation of missing values
3. Balancing of the target classes

Feature preprocessing

Algorithms that don't change data, but reduce number of features

1. PCA
2. Linear SVM (non zero model coefficients)
3. Feature agglomeration
4. Random forest
5. Extremly randomized forest
6. ...

Feature preprocessing

Well-established classification algorithms

1. General linear models
2. SVM
3. Discriminant analysis
4. Nearest neighbors
5. Naive Bayes
6. Decision trees
7. Ensemble methods

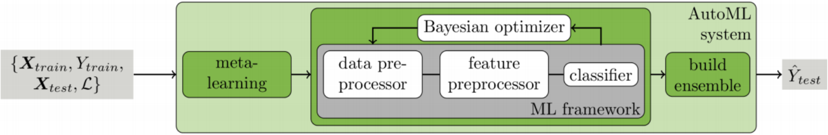
Auto-sklearn features result list

name	#λ	cat (cond)	cont (cond)
AdaBoost (AB)	3	-	3 (-)
Bernoulli naïve Bayes	2	1 (-)	1 (-)
decision tree (DT)	3	1 (-)	2 (-)
extreml. rand. trees	5	2 (-)	3 (-)
Gaussian naïve Bayes	-	-	-
gradient boosting (GB)	6	-	6 (-)
kNN	3	2 (-)	1 (-)
LDA	2	-	2 (-)
linear SVM	5	3 (-)	2 (-)
kernel SVM	8	3 (-)	5 (2)
multinomial naïve Bayes	2	1 (-)	1 (-)
passive aggressive	3	1 (-)	2 (-)
QDA	2	-	2 (-)
random forest (RF)	5	2 (-)	3 (-)
ridge regression (RR)	2	-	2 (-)
SGD	9	3 (-)	6 (3)

name	#λ	cat (cond)	cont (cond)
extreml. rand. trees prepr.	5	2 (-)	3 (-)
fast ICA	4	3 (-)	1 (-)
feature agglomeration	3	2 (-)	1 (-)
kernel PCA	5	1 (-)	4 (3)
rand. kitchen sinks	2	-	2 (-)
linear SVM prepr.	5	3 (-)	2 (-)
no preprocessing	-	-	-
nystroem sampler	5	1 (-)	4 (3)
PCA	2	1 (-)	1 (-)
random trees embed.	4	-	4 (-)
select percentile	2	1 (-)	1 (-)
select rates	3	2 (-)	1 (-)
imputation	1	1 (-)	-
balancing	1	1 (-)	-
rescaling	1	1 (-)	-

aad_freiburg approach

This guy added two more stages:



Meta-Learning

This is used to warm-start Bayesian optimizer

1. Given 140 datasets, compute it's metafeatures (total 38)
    - Simple features (N samples, N features, N classes etc)

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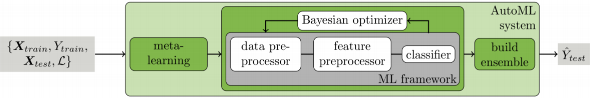
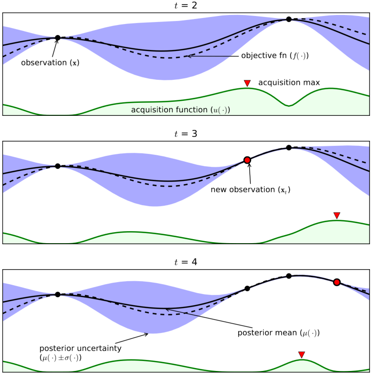
Bayesian optimization reminder





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After Bayesian optimization one gets set of ML frameworks:

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Auto-sklearn results