2019-0703 IST 707 Data Analytics

Homework Assignment 7 (week 8)

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Assignment: SVMs, kNN, and Random Forest for handwritting recognition

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1 Introduction

Recognize digits 0 to 9 in handwriting images. Use the sampled data to construct prediction models using SVMs, kNN and Random Forest algorithms. Compare their performance with Naive Bayes and Decision Tree models built in week seven's homework six assignment.

The success metric is evaluated on the categorization accuracy of the predictions (the percentage of images predicted correctly).

1.1 About the Data

The data files train.csv and test.csv contain gray-scale images of hand-drawn digits, from zero through nine.

Each image is 28 pixels in height and 28 pixels in width, for a total of 784 pixels in total. Each pixel has a single pixel-value associated with it, indicating the lightness or darkness of that pixel, with higher numbers meaning darker. This pixel-value is an integer between 0 and 255, inclusive.

The training data set, (train.csv), has 785 columns. The first column, called "label", is the digit that was drawn by the user. The rest of the columns contain the pixel-values of the associated image.

Each pixel column in the training set has a name like pixelx, where x is an integer between 0 and 783, inclusive. To locate this pixel on the image, suppose that we have decomposed x as x = i * 28 + j, where i and j are integers between 0 and 27, inclusive. Then pixelx is located on row i and column j of a 28 x 28 matrix, (indexing by zero).

For example, pixel31 indicates the pixel that is in the fourth column from the left, and the second row from the top, as in the ascii-diagram below.

Visually, if we omit the "pixel" prefix, the pixels make up the image like this:

000 001 002 003 ... 026 027

028 029 030 031 ... 054 055

056 057 058 059 ... 082 083

| | | | ... | |

728 729 730 731 ... 754 755

756 757 758 759 ... 782 783

The test data set, (test.csv), is the same as the training set, except that it does not contain the "label" column.

1.2 Dataset Info

- Kaggel full training dataset has 42,000 rows and 785 columns

- Kaggel full testing dataset has 28,000 rows and 785 columns
- Kaggel subsampled training dataset has 1,400 rows and 785 columns
- Kaggel subsample testing dataset has 1,000 rows and 785 columns

For this exercise, the full training and testing datasets were used.

1.3 Data Exploration

There were no NaN fields in the either the kaggel full training or kaggel full testing datasets.

Number of class labels: 10

Number of pixels: 784

Full training dataset info:

RangeIndex: 42000 entries, 0 to 41999
Columns: 785 entries, label to pixel783
dtypes: int64(785)
memory usage: 251.5 MB

Full testing dataset info:

RangeIndex: 28000 entries, 0 to 27999
Columns: 785 entries, label to pixel783
dtypes: int64(784), object(1)
memory usage: 167.7+ MB

1.3.1 *Random Sampling of Training Dataset Images*

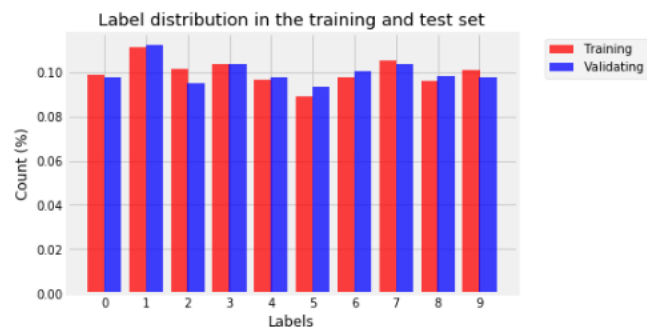
Figure: Sample Training Digit Images

Figure: Sample Digit Variations

1.4 Data Transformation

The full training dataset was split into training/validation (80/20 split) sets for model validation and prediction accuracy measurement. The test dataset provided does not have labeled classifications to be used for model validation. It is the unseen data used by the Kaggel competition for submission of predicted classification. In section five, this unseen dataset is used for the competition submission predicitons.

The training/testing datasets created from splitting the full training dataset have nearly equal number of each class label. These datasets are considered balanced.



1.4.1 *Data Normalization*

The 'label' attribute was encoded to a catagorical, nominal variable for class classification training/testing. This was done using the sklearn.preprocessing.LabelEncoder class. Encode labels with value between 0 and n_classes-1.

Training and test dataset's were converted to float32 objects to minimizing memory computation needs and normalized from RGB color to black and white (0-1). This was accomplished by dividing the training and test data by 255.

2 Model - Support Vector Machine

Python Package: scikit-learn v0.21.3 sklearn.svm.SVC

2.1 Analysis and Models

2.1.1 *Data Preprocessing*

Data preprocessing for this model is described above in section 1.4.

2.2 Model - Support Vector Classification

Python Package: scikit-learn v0.21.3 sklearn.svm.SVC

SVMs are a set of supervised learning methods used for classification, regession and outliers detection. For this implementation we are using it as a multi-class classifier.

2.2.1 *Model Details*

C-Support Vector Classification. The implementation of this class is based on libsvm. The multiclass support is handled according to a one-vs-one scheme.

2.2.1.1 Model Parameters

For this model, all default parameters were selected. Below is a listing of those parameters.

Parameter and Value	Description
C=1.0	Penalty parameter C of the error term.
cache_size=200	Specify the size of the kernel cache (in MB).
class_weight=None	Set the parameter C of class i to class_weight[i]*C for SVC. If not given, all classes are supposed to have weight one. The “balanced” mode uses the values of y to automatically adjust weights inversely proportional to class frequencies in the input data as n_samples / (n_classes * np.bincount(y))
coef0=0.0	Independent term in kernel function. It is only significant in ‘poly’ and ‘sigmoid’.
decision_function_shape='ovr'	Whether to return a one-vs-rest (‘ovr’) decision function of shape (n_samples, n_classes) as all other classifiers, or the original one-vs-one (‘ovo’) decision function of libsvm which has shape (n_samples, n_classes * (n_classes - 1) / 2). However, one-vs-one (‘ovo’) is always used as multi-class strategy.
degree=3	Degree of the polynomial kernel function (‘poly’). Ignored by all other kernels.

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gamma='auto'	Kernel coefficient for 'rbf', 'poly' and 'sigmoid'. Current default is 'auto' which uses 1 / n_features, if gamma='scale' is passed then it uses 1 / (n_features * X.var()) as value of gamma.
kernel='rbf'	Specifies the kernel type to be used in the algorithm. It must be one of 'linear', 'poly', 'rbf', 'sigmoid', 'precomputed' or a callable.
max_iter=-1	Hard limit on iterations within solver, or -1 for no limit.
probability=False	Whether to enable probability estimates. This must be enabled prior to calling fit, and will slow down that method.
random_state=None	The seed of the pseudo random number generator used when shuffling the data for probability estimates. If int, random_state is the seed used by the random number generator; If RandomState instance, random_state is the random number generator; If None, the random number generator is the RandomState instance used by np.random.
shrinking=True	Whether to use the shrinking heuristic.
tol=0.001	Tolerance for stopping criterion.
verbose=True	Enable verbose output. Note that this setting takes advantage of a per-process runtime setting in libsvm that, if enabled, may not work properly in a multithreaded context.

2.2.1.2 Model Results

Fit Score	% Accuracy	Fit Time	Score Time	Predict Time	Precision	Recal	F1-Score
0.935	94%	267.03898	189.21377	192.75343	0.94	0.94	0.94

<u>Classification Report:</u>

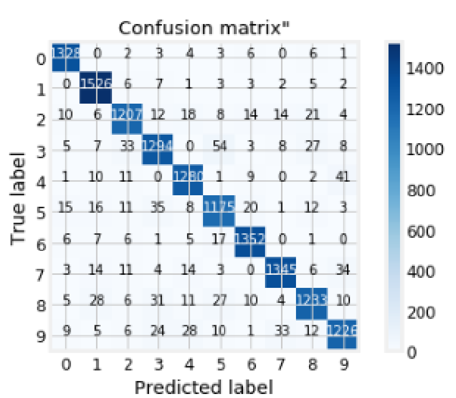
```
              precision    recall  f1-score   support

      Class0       0.96      0.98      0.97      1353
      Class1       0.94      0.98      0.96      1555
      Class2       0.93      0.92      0.92      1314
      Class3       0.92      0.90      0.91      1439
      Class4       0.93      0.94      0.94      1355
      Class5       0.90      0.91      0.90      1296
      Class6       0.95      0.97      0.96      1395
      Class7       0.96      0.94      0.95      1434
      Class8       0.93      0.90      0.92      1365
      Class9       0.92      0.91      0.91      1354

    accuracy                           0.94     13860
   macro avg       0.94      0.93      0.93     13860
weighted avg       0.94      0.94      0.94     13860
```

Confusion Matrix Report:

```
SVM Base Confusion Matrix Report:
[[1328    0    2    3    4    3    6    0    6    1]
 [   0 1526    6    7    1    3    3    2    5    2]
 [  10    6 1207   12   18    8   14   14   21    4]
 [   5    7   33 1294    0   54    3    8   27    8]
 [   1   10   11    0 1280    1    9    0    2   41]
 [  15   16   11   35    8 1175   20    1   12    3]
 [   6    7    6    1    5   17 1352    0    1    0]
 [   3   14   11    4   14    3    0 1345    6   34]
 [   5   28    6   31   11   27   10    4 1233   10]
 [   9    5    6   24   28   10    1   33   12 1226]]
```



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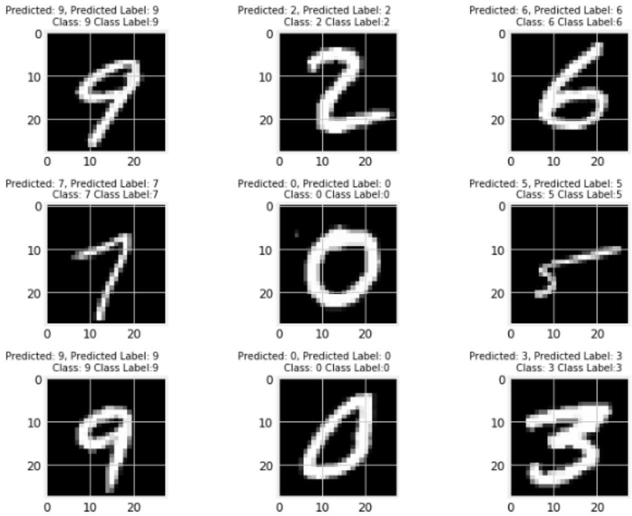
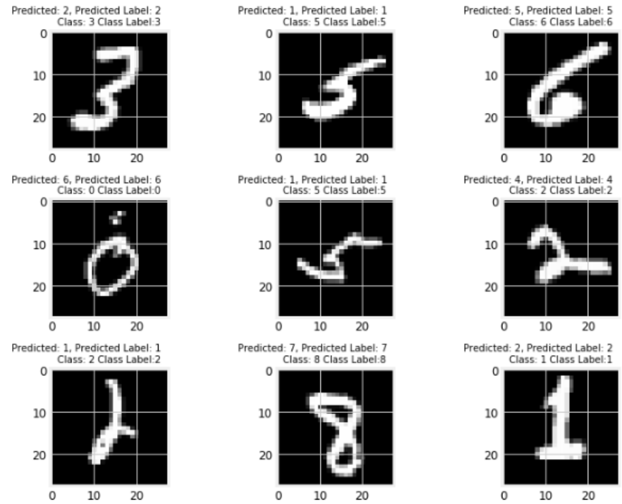
Sample of Accurately Predicted Digits:



Sample of Inaccurately Predicted Digits:



3 Model - KNeighbors Classifier

Python Package: scikit-learn v0.21.3 sklearn.neighbors.KNeighborsClassifier

3.1 Analysis and Models

3.1.1 *Data Preprocessing*

Data preprocessing for this model is described above in section 1.4.

3.2 Model - kNN

Classifier implementing the k-nearest neighbors vote. This classifier is well-adapted to complex, highly nonlinear datasets such as this hand written digits images dataset. The idea of K-nearest neighbors is; given a new point in the feature space, find the K closest points from the training set and assign the label of the majority of those points. In our base model, we are using the Euclidean distance metric.

An import note, is that no model is learned by a K-nearest neighbor algorithm. The classifier just stores all data points and compares any new target points with them. This is an example of instance-based learning. It is in contrast to other classifiers. This classifier is computationally intensive with a large training dataset such as the MNIST digits dataset because a large number of distances have to be computed for testing.

3.2.1 *Model Details*

KNeighborsClassifier implements learning based on the k nearest neighbors of each query point, where k is an integer value specified at object creation as a parameter input. The optimal choice of the value k is highly data-dependent: in general a larger k suppresses the effects of noise, but makes the classification boundaries less distinct. This implementation uses basic concepts, where the nearest neighbors classification uses uniform weights. The value assigned to a query point is computed from a simple majority vote of the nearest neighbors.

```
kNN_base.get_params()
{'algorithm': 'auto',
 'leaf_size': 30,
 'metric': 'minkowski',
 'metric_params': None,
 'n_jobs': None,
 'n_neighbors': 5,
 'p': 2,
 'weights': 'uniform'}
```

3.2.1.1 Model Parameters

For this model, all default parameters were selected. Below is a listing of those parameters.

Parameter and Value	Description
n_neighbors=5	Number of neighbors to use by default for kneighbors queries
weights="uniform"	weight function used in prediction. ‘uniform’ : uniform weights. All points in each neighborhood are weighted equally.
algorithm="auto"	Algorithm used to compute the nearest neighbors - ‘auto’ will attempt to decide the most appropriate algorithm based on the values passed to fit method.
leaf_size=30	Leaf size passed to BallTree or KDTree. This can affect the speed of the construction and query, as well as the memory required to store the tree. The optimal value depends on the nature of the problem.
p=2	Power parameter for the Minkowski metric. When p = 1, this is equivalent to using manhattan_distance (l1), and euclidean_distance (l2) for p = 2
metric="minkowski"	The distance metric to use for the tree. The default metric is minkowski, and with p=2 is equivalent to the standard Euclidean metric.
metric_params=None	Additional keyword arguments for the metric function.
n_jobs=None	The number of parallel jobs to run for neighbors search. None means 1

3.2.1.2 Model Results

Fit Score	% Accuracy	Fit Time	Score Time	Predict Time	Precision	Recal	F1-Score
0.964	96%	5.9340	609.41129	537.32265	0.96	0.96	0.96

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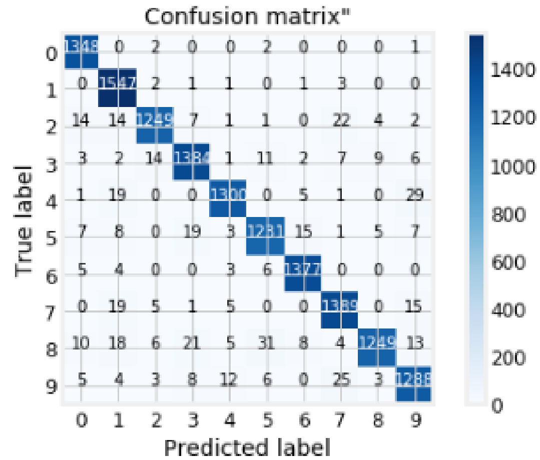
Classification Report:

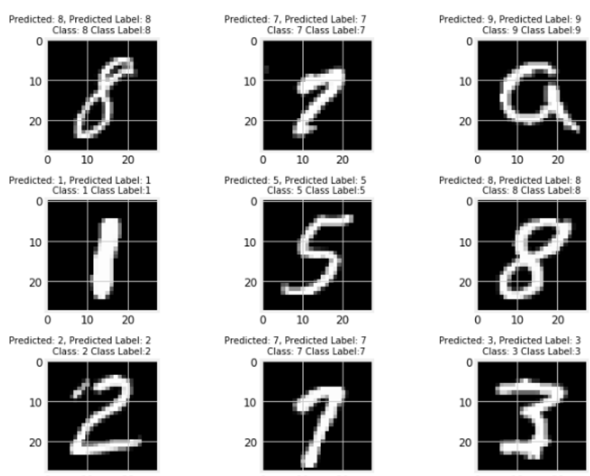
	precision	recall	f1-score	support
Class0	0.97	1.00	0.98	1353
Class1	0.95	0.99	0.97	1555
Class2	0.98	0.95	0.96	1314
Class3	0.96	0.96	0.96	1439
Class4	0.98	0.96	0.97	1355
Class5	0.96	0.95	0.95	1296
Class6	0.98	0.99	0.98	1395
Class7	0.96	0.97	0.96	1434
Class8	0.98	0.92	0.95	1365
Class9	0.95	0.95	0.95	1354
accuracy			0.96	13860
macro avg	0.96	0.96	0.96	13860
weighted avg	0.96	0.96	0.96	13860

Confusion Matrix Report:

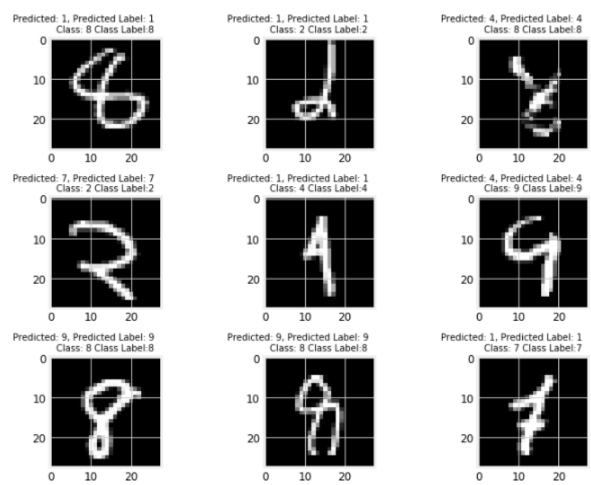
```
K-Nearest Neighbors Base Classification:
[[1348    0    2    0    0    2    0    0    0    1]
 [   0 1547    2    1    1    0    1    3    0    0]
 [  14   14 1249    7    1    1    0   22    4    2]
 [   3    2   14 1384    1   11    2    7    9    6]
 [   1   19    0    0 1300    0    5    1    0   29]
 [   7    8    0   19    3 1231   15    1    5    7]
 [   5    4    0    0    3    6 1377    0    0    0]
 [   0   19    5    1    5    0    0 1389    0   15]
 [  10   18    6   21    5   31    8    4 1249   13]
 [   5    4    3    8   12    6    0   25    3 1288]]
```



Sample of Accurately Predicted Digits:



Sample of Inaccurately Predicted Digits:



4 Model - Random Forest Classification

4.1 Model - RandomForestClassifier

Python Package: scikit-learn v0.21.3 [sklearn.ensemble.RandomForestClassifier]

A random forest is a meta estimator that fits a number of decision tree classifiers on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting. The sub-sample size is always the same as the original input sample size but the samples are drawn with replacement if bootstrap=True (default).

4.2 Analysis and Models

4.2.1 *Data Preprocessing*

Data preprocessing for this model is described above in section 1.4.

4.3 Model - Random Forest

This algorithm uses a perturb-and-combine techniques specifically designed for trees. A diverse set of classifieres are created by introducing randomness in the classifier construction. The prediction of the ensemble is given as the averaged prediction of the individual classifiers. Like decision trees, forests of trees also extend to multi-output problems. In random forests, each tree in the ensemble is built from a sample drawn with replacement. When splitting each node during the construction of a tree, the best split is found either from all input features or a random subset of size max_features.

4.3.1 *Model Details*

rf_base.get_params(deep=True):

```
{'bootstrap': True,
 'class_weight': None,
 'criterion': 'gini',
 'max_depth': None,
 'max_features': 'auto',
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_impurity_split': None,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 100,
 'n_jobs': None,
 'oob_score': False,
 'random_state': None,
 'verbose': 2,
 'warm_start': False}
```

4.3.1.1 Model Parameters

For this model, all default parameters were selected. Below is a listing of those parameters. For parameter tuning techniques, see this for more details.

Parameter and Value	Description
n_estimators=100	The number of trees in the forest.
criterion="gini"	The function to measure the quality of a split. Supported criteria are “gini” for the Gini impurity and “entropy” for the information gain.
max_depth=None	The maximum depth of the tree. If None, then nodes are expanded until all leaves are pure or until all leaves contain less than min_samples_split samples
min_samples_split=2	The minimum number of samples required to split an internal node
min_samples_leaf=1	The minimum number of samples required to be at a leaf node. A split point at any depth will only be considered if it leaves at least min_samples_leaf training samples in each of the left and right branches
min_weight_fraction_leaf=0.0	The minimum weighted fraction of the sum total of weights (of all the input samples) required to be at a leaf node. Samples have equal weight when sample_weight is not provided.
max_features="auto"	The number of features to consider when looking for the best split: If “auto”, then max_features=sqrt(n_features).
max_leaf_nodes=None	Grow trees with max_leaf_nodes in best-first fashion. Best nodes are defined as relative reduction in impurity. If None then unlimited number of leaf nodes.
min_impurity_decrease=0.0	A node will be split if this split induces a decrease of the impurity greater than or equal to this value.
min_impurity_split=None	Threshold for early stopping in tree growth. A node will split if its impurity is above the threshold, otherwise it is a leaf.
bootstrap=True	Whether bootstrap samples are used when building trees. If False, the whole datset is used to build each tree.
oob_score=False	Whether to use out-of-bag samples to estimate the generalization accuracy.
n_jobs=None	The number of jobs to run in parallel for both fit and predict. None means 1 unless in a joblib.parallel_backend context. -1 means using all processors.
random_state=None	if int, random_state is the seed used by the random number generator; If RandomState instance, random_state is the random number generator; If None, the random number generator is the RandomState instance used by np.random
verbose=2	Controls the verbosity when fitting and predicting.
warm_start=False	When set to True, reuse the solution of the previous call to fit and add more estimators to the ensemble, otherwise, just fit a whole new forest.

class_weight=None	Weights associated with classes in the form {class_label: weight}. If not given, all classes are supposed to have weight one. For multi-output problems, a list of dicts can be provided in the same order as the columns of y.

The main parameters to adjust when using these methods is n_estimators and max_features. The former is the number of trees in the forest. The larger the better, but also the longer it will take to compute. Also, the results will stop getting significantly better beyone a critical number of trees. The later is the size of the random subsets of features to consider when splitting a node. The lower the greater the reduction of variance, but also the greater the increase in bias.

4.3.1.2 Model Results

Fit Score	% Accuracy	Fit Time	Score Time	Predict Time	Precision	Recal	F1-Score
0.9624	96%	25.2947	0.8023	0.8072	0.96	0.96	0.96

Classification Report:

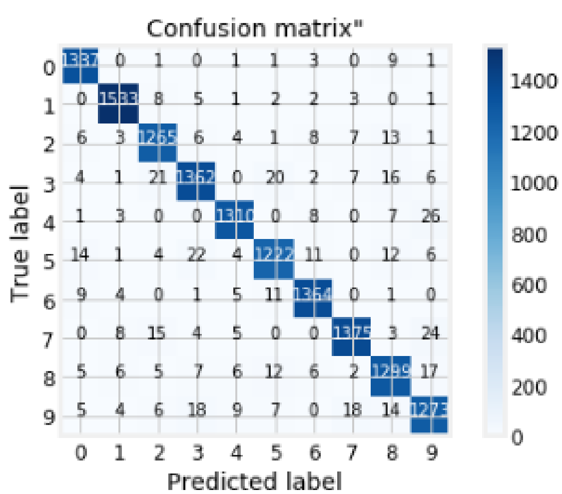
```
              precision    recall  f1-score   support

      Class0       0.97      0.99      0.98      1353
      Class1       0.98      0.99      0.98      1555
      Class2       0.95      0.96      0.96      1314
      Class3       0.96      0.95      0.95      1439
      Class4       0.97      0.97      0.97      1355
      Class5       0.96      0.94      0.95      1296
      Class6       0.97      0.98      0.97      1395
      Class7       0.97      0.96      0.97      1434
      Class8       0.95      0.95      0.95      1365
      Class9       0.94      0.94      0.94      1354

    accuracy                           0.96     13860
   macro avg       0.96      0.96      0.96     13860
weighted avg       0.96      0.96      0.96     13860
```

Confusion Matrix Report:

```
SVM Base Confusion Matrix Report:
[[1337    0    1    0    1    1    3    0    9    1]
 [   0 1533    8    5    1    2    2    3    0    1]
 [   6    3 1265    6    4    1    8    7   13    1]
 [   4    1   21 1362    0   20    2    7   16    6]
 [   1    3    0    0 1310    0    8    0    7   26]
 [  14    1    4   22    4 1222   11    0   12    6]
 [   9    4    0    1    5   11 1364    0    1    0]
 [   0    8   15    4    5    0    0 1375    3   24]
 [   5    6    5    7    6   12    6    2 1299   17]
 [   5    4    6   18    9    7    0   18   14 1273]]
```



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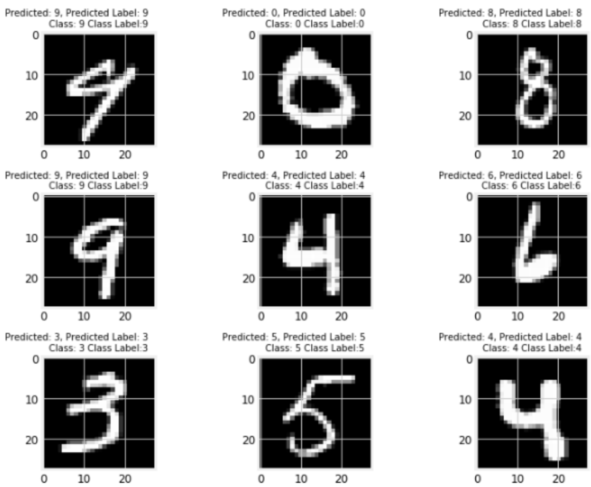
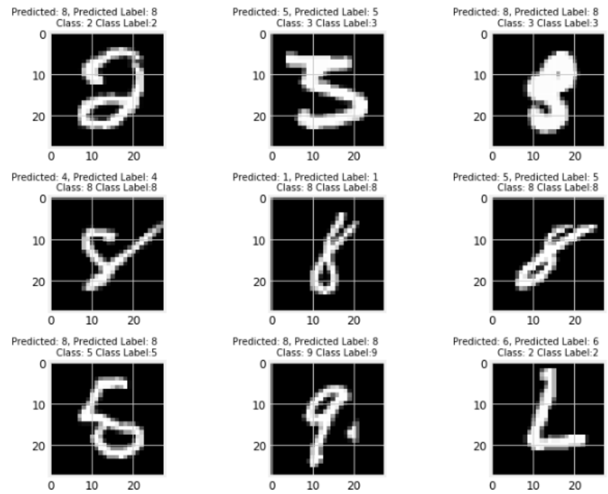
Sample of Accurately Predicted Digits:



Sample of Inaccurately Predicted Digits:



5 Model Comparison

Recognize digits 0 to 9 in handwriting images. Use the sampled data to construct prediction models using SVMs, kNN and Random Forest algorithms. Compare their performance with Naive Bayes and Decision Tree (cnb_cv, gnb_cv, dtc_cv) models built in week seven's homework six assignment.

The success metric is evaluated on the categorization accuracy of the predictions (the percentage of images predicted correctly).

Overall, the KNeighbors Classifier had a marginally higher accuracy score then the Random Forest Classifier making it the best predictor model of this dataset. That is if compute time isn't a choice factor. Due to that the kNN classifier is an instance-based learner, it takes a much longer compute time, when scoring and predicting datasets, then other classifiers. Compared with the Naive Bayes and Decision Tree models, these new models, SVMs, kNNs, and Random Forests, all out performed them significantly. Most likely this is due to the hyperparameter configurations of each model used during this round of testing. For simple baseline comparison, mostly default parameters were used. Further trials should be conducted testing various hyperparamter settings to see if any change this outcome.

Model Performance Ranking Table, sorted by PredictAccuracyScore descending:

	Name	TestAccuracyScore	PredictAccuracyScore	FitTime	ScoreTime	PredictTime	TotalTime
2	kNN_base	0.964069	0.964069	3.746577	479.127499	471.450553	954.324630
1	rf_base	0.963276	0.963276	21.162543	0.679343	0.681922	22.523808
3	dtc_cv	0.843660	0.947403	9.689057	0.125913	0.055994	9.870964
0	svc_base	0.935498	0.935498	234.364119	149.542525	151.982448	535.889092
4	cnb_cv	0.750096	0.717027	0.489532	0.141118	0.082912	0.713562
5	gnb_cv	0.674029	0.570924	0.902207	3.501948	1.651511	6.055666

Model Performance Ranking Table, sorted by FitTime, ScoreTime, PredictTime ascending:

	Name	TestAccuracyScore	PredictAccuracyScore	FitTime	ScoreTime	PredictTime	TotalTime
4	cnb_cv	0.750096	0.717027	0.489532	0.141118	0.082912	0.713562
5	gnb_cv	0.674029	0.570924	0.902207	3.501948	1.651511	6.055666
3	dtc_cv	0.843660	0.947403	9.689057	0.125913	0.055994	9.870964
1	rf_base	0.963276	0.963276	21.162543	0.679343	0.681922	22.523808
0	svc_base	0.935498	0.935498	234.364119	149.542525	151.982448	535.889092
2	kNN_base	0.964069	0.964069	3.746577	479.127499	471.450553	954.324630

6 Kaggle Test Result

6.1 Submission File Format

The submission file should be in the following format: For each of the 28000 images in the test set, output a single line containing the ImageId and the digit predicted. For example, if predict that the first image is of a 3, the second image is of a 7, and the third image is of a 8, then the submission file would look like:

ImageId,Label
1,3
2,7
3,8
(27997 more lines)

The evaluation metric for this contest is the categorization accuracy, or the proportion of test images that are correctly classified. For example, a categorization accuracy of 0.97 indicates that, all but 3% of the images have been correctly classified.

Based on the above best accuracy model, KNeighbors Classifier, the associated kNN_submission.csv file was generated using the kNN model to predict class labels of the held out kaggel test dataset.

Sample submission head:

	ImageId	Label
0	1	2
1	2	0
2	3	9
3	4	9
4	5	3
5	6	7
6	7	0
7	8	3
8	9	0
9	10	3

7 Appendix - Decision Tree (hw 6) Models

7.1 Analysis and Models

7.1.1 *Data Preprocessing*

To minimize memory consumption, the datasets attributes were reduced to int32 objects from int64.

7.2 Model - DecisionTreeClassifier

Python package: [scikit-learn sklearn.tree.DecisionTreeClassifier]

7.2.1 *Model Details*

This DecisionTreeClassifier represents a baseline measurement for the Cross-Validation model detailed in seciont 2.3. The model is fit (trained on) the training dataset described in section 1.1.2 above. (i.e., train_test_split method)

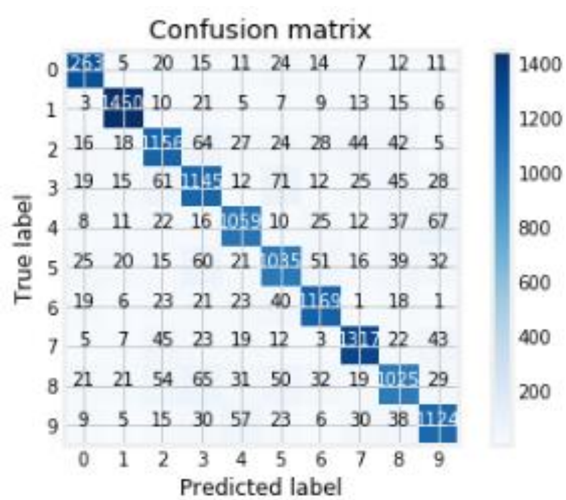
7.2.1.1 Model Parameters

As a baseline model, all default parameters were used in it's build. As such, the default values for the parameters controlling the size of the trees (max_depth, min_samples_leaf) lead to fully grown and unpruned trees; which on this data set lead to very large trees.

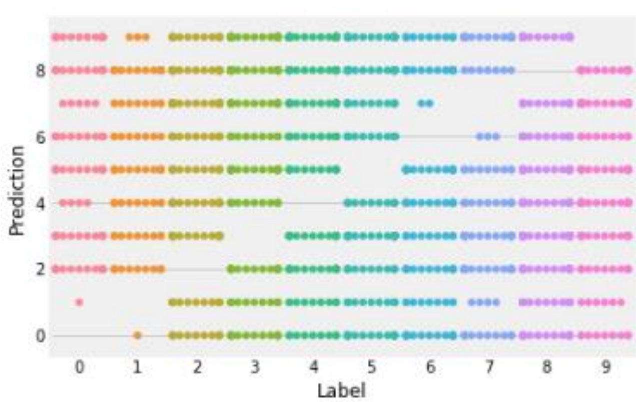
To obtain a deterministic behavior during fitting, random_state was fixed to 0.

7.2.1.2 Model Results

- Fit Score: [0.84726] - 84.7%
- Fit Time: [9.80047]
- Score Time: [0.05957]
- Predict Time: [0.10187]
- Percent Accurately Labeled: [0.84726]



Misclassified Labels:



7.3 Model - DecisionTreeClassifier with Cross-Validation

To avoid the risk of overfitting on a standard test set, cross-validation is used as a means of subdividing the training dataset to hold out a validation set. Training proceeds on the training set, after which evaluation is done on the validation set, when the trials are complete and seem successful, final evaluation is done on the held out test set. In this approach, called k-fold CV, the training set is split into k smaller sets. A model is trainined using k-1 of the folds as training data; the resulting model is validated on the remaining part of the data. (i.e., it is used as a test set to compute a performance measure such as accuracy).

7.3.1 *Model Details*

This is a DecisionTreeClassifier with Cross-Validation. Training and validation are performed on the full training dataset (i.e., without train_test_split methods) using cross-validation procedures. For final evaluation, the held out test set from the train_test_split procedures is used for prediction accuracy measurement. The held out kaggle full test dataset is used for final prediction and competition submission.

7.3.2 *Model Parameters*

The DecisionTreeClassifier object is instantiated with default parameters and random_state equal to 0. Cross validation is used for training and scoring the model with cross validation parameters set to 3. This created three experiments. Overall execution time to process this cross validation procedure with three folds was 33.63 seconds.

Note that cross validation parameters, return_train_score and return_estimator were set to True to report on performance metrics. These parameters increase process execution time by 10 plus seconds.

7.3.3 *Model Results*

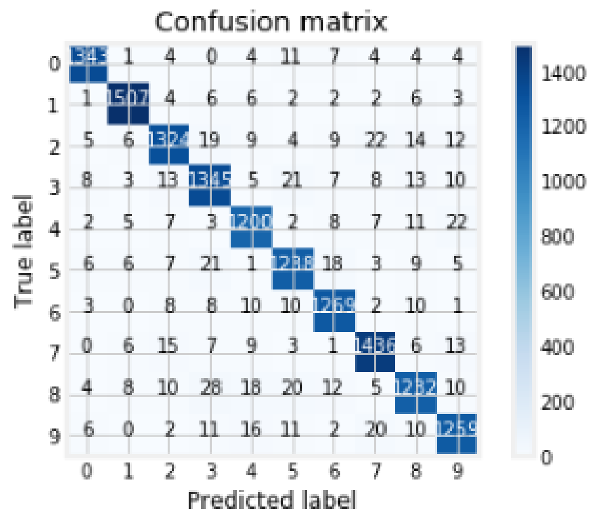
<u>Three fold, Cross Validation Metrics:</u>

Fit Time:	[11.02870226, 10.70894098, 10.53186178]
Score Time:	[0.11198735, 0.10233521, 0.1799221]
Test Recall Scores:	[0.84261269, 0.84340589, 0.84338957]
Test Precision Scores:	[0.84285837, 0.8436598, 0.84341631]
Train Recall Scores:	[1., 1., 1.]
Train Precision Scores:	[1., 1., 1.]

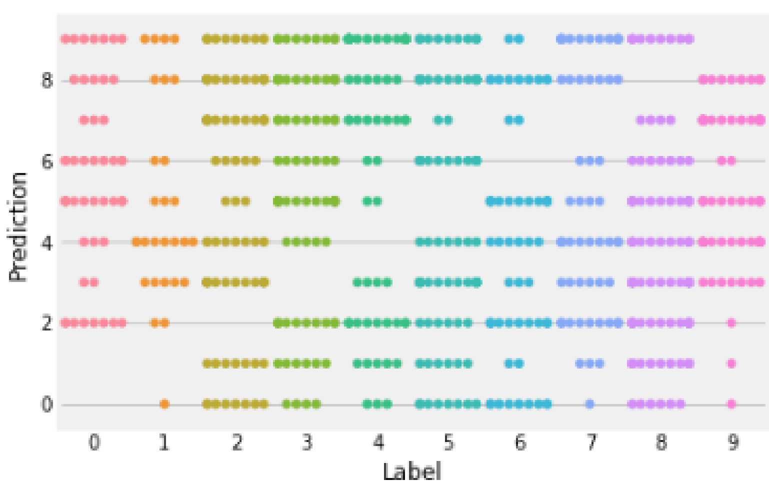
For comparision to the baseline DecisionTreeClassifier, the experment with the best test precision recall was used to predict class labels on the test dataset from the train_test_split procedures.

It's percent accuracy on class labeling was: [0.94898]

*The 10% increase in accuracy is most likely due to overfitting.



<u>Misclassified Labels:</u>



8 Appendix - Naive Bayes (hw6) Models

*T*he **sklearn.naive_bayes** module implements Naive Bayes algorithms. These are supervised learning methods based on applying Bayes' theorem with strong (naive) feature independence assumptions.

8.1 Analysis and Models

8.1.1 *Data Preprocessing*

No additional data preprocessing we done for the Naive Bayes Models.

8.2 Model - Gaussian Naive Bayes Classifier

GaussianNB implements the Gaussian Naive Bayes algorithm for classification. The likelihood of the features is assumed to be Gaussian:

8.2.1 *Model Details*

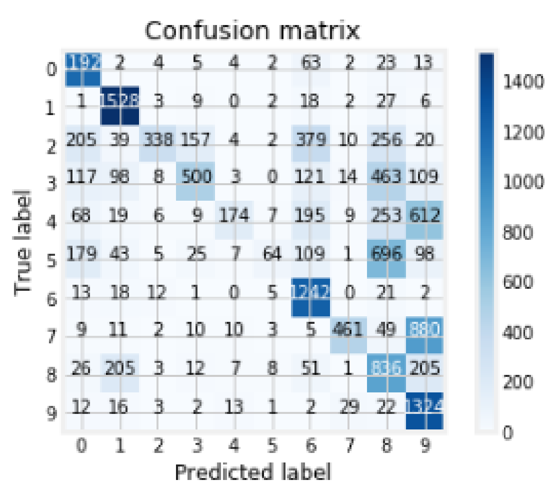
This Gaussian Naive Bayes Classifier represents a baseline measurement for the Cross-Validation model detailed in section 3.4. The model is fit (trained on) the training dataset described in section 1.1.2 above. (i.e., train_test_split method)

8.2.2 *Model Parameters*

As a baseline model, all default parameters were used in it's build.

8.2.3 *Model Results*

- Fit Score: [0.5526] - 55.2%
- Fit Time: [0.5442]
- Score Time: [1.8223]
- Predict Time: [1.7563]
- Percent Accurately Labeled: [0.5525] - 55.2%



8.3 Model - Complement Naive Bayes Classifier

The Complement Naive Bayes classifier was designed to correct the “severe assumptions” made by the standard Multinomial Naive Bayes classifier. It is particularly suited for imbalanced data sets.

8.3.1 *Model Details*

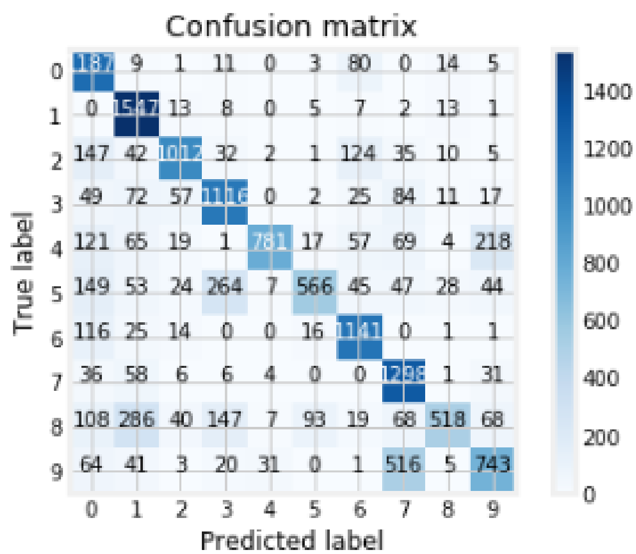
This Complement Naive Bayes Classifier represents a baseline measurement for the Cross-Validation model detailed in section 3.5 as well as a comparison to the Gaussian Naive Bayes Classifier. The model is fit (trained on) the training dataset described in section 1.1.2 above. (i.e., train_test_split method)

8.3.2 *Model Parameters*

As a baseline model, all default parameters were used in it's build.

8.3.3 *Model Results*

- Fit Score: [0.714935] - 71.5%
- Fit Time: [0.192643]
- Score Time: [0.079123]
- Predict Time: [0.076702]
- Percent Accurately Labeled: [0.71493]



8.4 Model - Gaussian Naive Bayes Classifier with CV

8.4.1 *Model Details*

This is a Gaussian Naive Bayes Classifier with Cross-Validation. Training and validation are performed on the full training dataset (i.e., without train_test_split methods) using cross-validation procedures. For final evaluation, the held out test set from the train_test_split procedures is used for prediction accuracy measurement. The held out kaggle full test dataset is used for final prediction and competition submission.

8.4.2 *Model Parameters*

The GaussianNaiveBayes object is instantiated with default parameters. Cross validation is used for training and scoring the model with cross validation parameters set to 3. This created three experiments. Overall execution time to process this cross validation procedure with three folds was 34.4 seconds.

Note that cross validation parameters, return_train_score and return_estimator were set to True to report on performance metrics. These parameters increase process execution time by 10 plus seconds.

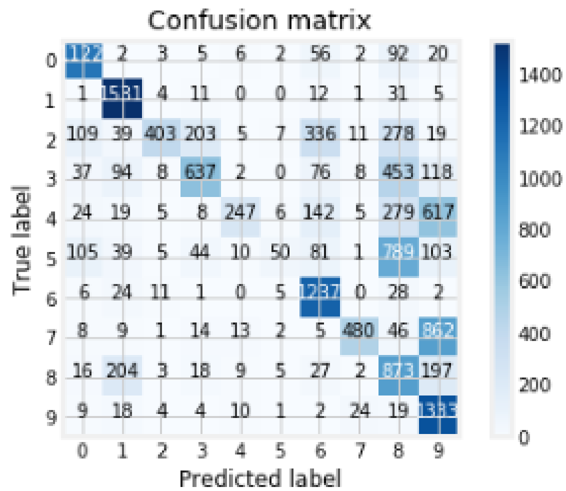
8.4.3 *Model Results*

<u>Three fold, cross validation results:</u>

Fit Time:	[0.90220666, 0.80869913, 0.8218224]
Score Time:	[3.50194836, 3.44823194, 4.44742441]
Test Recall Scores:	[0.55655069, 0.54957274, 0.55724842]
Test Precision Scores:	[0.6740292, 0.66896641, 0.66588789]
Train Recall Scores:	[0.56147661, 0.54797522, 0.56196516]
Train Precision Scores:	[0.68486952, 0.67642211, 0.67696248]

<u>Best Results:</u>

- Fit Score: [0.67402] - 67.4%
- Fit Time: [0.90220]
- Score Time: [3.50194]
- Predict Time: [1.65151]
- Percent Accurately Labeled: [0.57092] - 57%



8.5 Model - Complement Naive Bayes Classifier with CV

8.5.1 *Model Details*

This is a Complement Naive Bayes Classifier with Cross-Validation. Training and validation are performed on the full training dataset (i.e., without train_test_split methods) using cross-validation procedures. For final evaluation, the held out test set from the train_test_split procedures is used for prediction accuracy measurement. The held out kaggle full test dataset is used for final prediction and competition submission.

8.5.2 *Model Parameters*

The ComplementNaiveBayes object is instantiated with default parameters. Cross validation is used for training and scoring the model with cross validation parameters set to 3. This created three experiments. Overall execution time to process this cross validation procedure with three folds was 2.83 seconds.

Note that cross validation parameters, return_train_score and return_estimator were set to True to report on performance metrics. These parameters increase process execution time by 10 plus seconds.

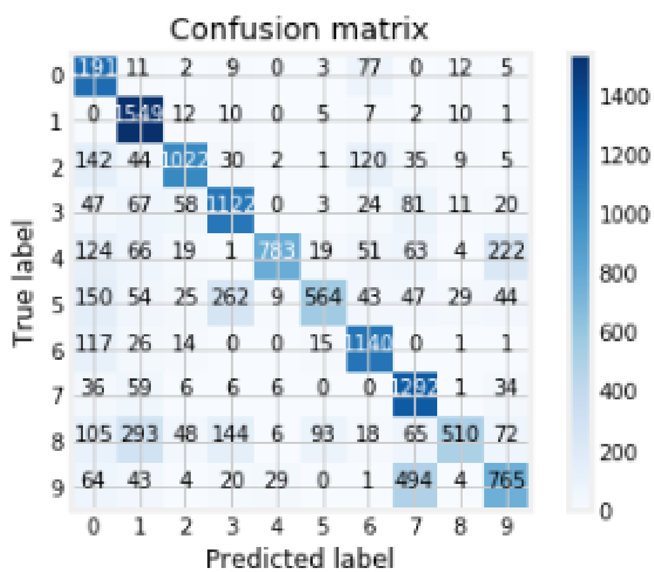
8.5.3 *Model Results*

<u>Three fold, cross validation results:</u>

Fit Time:	[0.48953247, 0.48158693, 0.45195508]
Score Time:	[0.14111781, 0.14356256, 0.15300584]
Test Recall Scores:	[0.71036493, 0.70859042, 0.70432896]
Test Precision Scores:	[0.75009572, 0.74860591, 0.74579701]
Train Recall Scores:	[0.70791525, 0.70864266, 0.71128889]
Train Precision Scores:	[0.74913705, 0.75059161, 0.75032785]

<u>Best Results:</u>

- Fit Score: [0.75009] - 75%
- Fit Time: [0.48953]
- Score Time: [0.14111]
- Predict Time: [0.08291]
- Accurately Labeled: [0.71702] - 71%



9 Appendix - Algorithm Performance Comparison (hw6)

Leaving the random forest algorathm out of this comparison, overall the decission tree algorithms performed better than the naive bayes algorithms, both complement and gaussian implementations, on this data set in predicting hand written digits 0 - 9. The decision tree with three cross fold validation had a 94.7% prediction accuracy to the test dataset and an 84.3% accuracy on the cross-validation test sets. The 10% increase in prediction accuracy over test accuracy is most likely due to overfitting.

Comparing performance speeds, the naive bayes algorithms out performed the decision tree algorithms substantually. Their speeds were computed in milliseconds, while the decission tree's were in seconds, with the random forest taking the longest at 21 seconds. This would be the result of the number of expermiments produced by the algorithms and how large the tree's could get. Without tuning the tree parameters they can grow very large.

Model Performance Ranking Table, sorted by PredictAccuracyScore descending:

	Name	TestAccuracyScore	PredictAccuracyScore	FitTime	ScoreTime	PredictTime
2	forest	0.963059	0.963059	21.031508	0.854076	0.792354
1	dtc_cv	0.843660	0.947403	9.689057	0.125913	0.055994
0	dtc	0.844805	0.844805	10.152261	0.075751	0.061106
6	cnb_cv	0.750096	0.717027	0.489532	0.141118	0.082912
4	cnb	0.714935	0.714935	0.192643	0.079123	0.076702
5	gnb_cv	0.674029	0.570924	0.902207	3.501948	1.651511
3	gnb	0.552597	0.552597	0.544163	1.822378	1.756255

Model Performance Ranking Table, sorted by FitTime, ScoreTime, PredictTime ascending:

	Name	TestAccuracyScore	PredictAccuracyScore	FitTime	ScoreTime	PredictTime
4	cnb	0.714935	0.714935	0.192643	0.079123	0.076702
6	cnb_cv	0.750096	0.717027	0.489532	0.141118	0.082912
3	gnb	0.552597	0.552597	0.544163	1.822378	1.756255
5	gnb_cv	0.674029	0.570924	0.902207	3.501948	1.651511
1	dtc_cv	0.843660	0.947403	9.689057	0.125913	0.055994
0	dtc	0.844805	0.844805	10.152261	0.075751	0.061106
2	forest	0.963059	0.963059	21.031508	0.854076	0.792354

10 Appendix - Grading Rubics

Grading rubrics:

1. Are the models constructed correctly?
2. Is the result analysis conclusion convincing?
3. Is sufficient details provided for others to repeat the analysis?
4. Does the analysis include irrelevant content?
5. Successful submission to Kaggle?