DATA MINING

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QUESTION 1

For this analysis we use Jupyter Notebook and the file is in IPython format. We downloaded "train.json"

a dataset with recipes from Kaggle and both this file and "classifiers.ipynb" exist in the same folder.

Analysis 1: Compare Classifier metrics CountVectorizer VS TfidfVectorizer

We work with the category "italian" and "mexican" at first, in order to make classifiers that differentiates different cuisines.

We extract features with two different techniques, **CountVectorizer** and **TfidfVectorizer** and compare the results for metrics such as **mean accuracy score**, **mean precision score**, **mean recall score**, **mean f1-measure score** and **mean confusion-matrix**.

The classifiers we use for this experiment are: **Logistic Regression, SVM, Decision Trees, K-NN, Naïve Bayes** and we use <u>5-Fold Cross Validation</u> to evaluate our prediction results.

```
****Logistic Regression mean scores COUNTVECTORIZER****
scores: {'fit_time': array([2.5504601 , 2.18405247, 2.21158576, 1.94333792, 1.90349221]),
'score_time': array([0.02898192, 0.02722764, 0.02730107, 0.02709079, 0.02767682]),
'test_accuracy': array([0.96288515, 0.96672504, 0.97162872, 0.96882662, 0.96812609])
'test_precision_weighted': array([0.96309073, 0.9668767, 0.97170751, 0.96893784, 0.96833373]), 'test_recall_weighted': array([0.96288515, 0.96672504, 0.97162872, 0.96882662, 0.96812609]),
'test_f1_weighted': array([0.96283275, 0.96668534, 0.97160427, 0.96879444, 0.96808231])}
mean score test accuracy: 0.967638326784304
mean score test precision weighted: 0.9677893006690403
mean score test recall weighted: 0.967638326784304
mean score test f1-measure weighted: 0.9675998230499061
Confusion Matrix: [[7683 155]
                     [ 307 613111
****Logistic Regression mean scores TFIDFVECTORIZER****
scores: {'fit_time': array([0.52974987, 0.52992105, 0.51307178, 0.4936018 , 0.5006001 ]),
'score_time': array([0.01318645, 0.00974274, 0.00974846, 0.00980425, 0.00980759]),
'test_accuracy': array([0.99264706, 0.99369527, 0.99194396, 0.99579685, 0.99334501]),
'test_precision_weighted': array([0.99274423, 0.99376687, 0.99206049, 0.99582877, 0.99342468]),
'test_recall_weighted': array([0.99264706, 0.99369527, 0.99194396, 0.99579685, 0.99334501]),
'test_f1_weighted': array([0.9926413 , 0.99369109, 0.99193702, 0.99579502, 0.9933403 ])}
mean score test accuracy: 0.993485628927578
mean score test precision weighted: 0.9935650103027747
mean score test recall weighted: 0.993485628927578
mean score test f1-measure weighted: 0.9934809442666724
Confusion Matrix: [[7838
                     [ 93 6345]]
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****SVM mean scores COUNTVECTORIZER****
scores: {'fit_time': array([0.4891715 , 0.49625278, 0.49789715, 0.5144918 , 0.49009752]),
'score_time': array([0.02744508, 0.02796507, 0.02731681, 0.02739477, 0.02725601]),
'test_accuracy': array([0.96113445, 0.96322242, 0.9614711 , 0.96532399, 0.96497373]),
'test_precision_weighted': array([0.96116578, 0.96322223, 0.9614711 , 0.96531882, 0.96497238]),
'test_recall_weighted': array([0.96113445, 0.96322242, 0.9614711 , 0.96532399, 0.96497373]),
'test f1 weighted': array([0.96110708, 0.96320787, 0.9614711 , 0.96532033, 0.96496109])}
mean score test accuracy: 0.9632251394428174
mean score test precision weighted: 0.9632300630213381
mean score test recall weighted: 0.9632251394428174
mean score test f1-measure weighted: 0.9632134975948101
Confusion Matrix: [[7597 241]
                      [ 284 615411
****SVM mean scores TFIDFVECTORIZER****
scores: {'fit_time': array([0.19516706, 0.19173741, 0.19179201, 0.19114351, 0.19552565]),
 score time': array([0.0107379 , 0.00990653, 0.00981736, 0.00994205, 0.00989962]),
**Test_accuracy': array([0.99614846, 0.99649737, 0.9943958, 0.9971979, 0.99579685]),

**test_precision_weighted': array([0.99617529, 0.99651958, 0.99445244, 0.9972056, 0.99582877]),

**test_recall_weighted': array([0.99614846, 0.99649737, 0.9943958, 0.9971979, 0.99579685]),
'test_f1_weighted': array([0.99614693, 0.99649612, 0.99439252, 0.9971973 , 0.99579502])}
mean score test accuracy: 0.9960072750641412
mean score test precision weighted: 0.9960363379540353
mean score test recall weighted: 0.9960072750641412
mean score test f1-measure weighted: 0.9960055765255399
Confusion Matrix: [[7837
                      [ 56 6382]]
****Decision-Tree mean scores COUNTVECTORIZER****
scores: {'fit_time': array([11.39658332, 33.20916319, 10.85297585, 11.07879996, 16.97399926]),
'score_time': array([0.02721238, 0.02717781, 0.02638102, 0.02665997, 0.02704692]),
'test_accuracy': array([0.93487395, 0.94535902, 0.93134851, 0.93870403, 0.94781086]),
'test_precision_weighted': array([0.93497916, 0.94541877, 0.9313223, 0.93869318, 0.94793324]),
'test_recall_weighted': array([0.93487395, 0.94535902, 0.93134851, 0.93870403, 0.94781086]),
'test f1 weighted': array([0.93490394, 0.94537721, 0.93131879, 0.93869756, 0.9477437 ])}
mean score test accuracy: 0.9396192732784883
mean score test precision weighted: 0.9396693301209688
mean score test recall weighted: 0.9396192732784883
mean score test f1-measure weighted: 0.9396082410941424
Confusion Matrix: [[7420 418]
                      [ 436 600211
****Decision-Tree mean scores TFIDFVECTORIZER****
scores: {'fit_time': array([2.93528199, 2.91533303, 2.83061743, 2.92146993, 2.83942223]),
 score time': array([0.01470017, 0.01477718, 0.01456809, 0.01467276, 0.01457882]),
'test accuracy': array([0.99894958, 0.99824869, 0.99754816, 0.99894921, 0.99859895]),
'test_precision_weighted': array([0.99895159, 0.99825055, 0.99755907, 0.99895122, 0.99860251]),
'test_recall_weighted': array([0.99894958, 0.99824869, 0.99754816, 0.99894921, 0.99859895]),
'test f1 weighted': array([0.99894947, 0.9982485 , 0.99754755, 0.9989491 , 0.99859875])}
mean score test accuracy: 0.9984589177177
mean score test precision weighted: 0.9984629859026336
mean score test recall weighted: 0.9984589177177
mean score test f1-measure weighted: 0.9984586754890283
Confusion Matrix: [[7837
                       [ 19 6419]]
****k-NN mean scores COUNTVECTORIZER****
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scores: {'fit_time': array([4.22745609, 4.12844706, 4.11732197, 4.16310835, 4.35632157]),
'score_time': array([173.40004349, 168.35602403, 170.35519505, 172.46086407, 171.29579973]),
'test_accuracy': array([0.88830532, 0.88406305, 0.88231173, 0.88721541, 0.87845884]),
'test_f1_weighted': array([0.8881997 , 0.88333008, 0.88132628, 0.8861979 , 0.87695044])}
mean score test accuracy: 0.884070871781287
mean score test precision weighted: 0.8871747597288895
mean score test recall weighted: 0.884070871781287
mean score test f1-measure weighted: 0.8832008807972722
Confusion Matrix: [[7345
                                   4931
                        [1162 5276]]
****k-NN mean scores TFIDFVECTORIZER****
scores: {'fit_time': array([2.26060057, 2.25794148, 2.25653839, 2.29463649, 2.26201057]),
'score_time': array([85.24381018, 85.42045975, 85.69957519, 85.78246546, 85.19833612]),
'test_accuracy': array([0.93277311, 0.92924694, 0.9352014, 0.94500876, 0.93309982]),
'test_recall_weighted': array([0.94010695, 0.93732614, 0.94204372, 0.95001376, 0.94036414]),
'test_recall_weighted': array([0.93277311, 0.92924694, 0.9352014, 0.94500876, 0.93309982]),
'test f1 weighted': array([0.93200522, 0.9283789 , 0.93450048, 0.94453364, 0.9323391 ])}
mean score test accuracy: 0.9350660053863928
mean score test precision weighted: 0.9419709424977883
mean score test recall weighted: 0.9350660053863928
mean score test f1-measure weighted: 0.9343514707413195
Confusion Matrix: [[7838
                        [ 927 5511]]
****Naive-Bayes mean scores COUNTVECTORIZER****
scores: {'fit_time': array([0.46336746, 0.48547864, 0.46542311, 0.45993423, 0.46202064]),
'score time': array([0.04326558, 0.02981758, 0.0301919, 0.02966714, 0.02948952]),
'test_accuracy': array([0.96358543, 0.96462347, 0.96497373, 0.96672504, 0.96532399])
'test_precision_weighted': array([0.96392113, 0.96502008, 0.96547506, 0.96698809, 0.96576285]),
'test_recall_weighted': array([0.96358543, 0.96462347, 0.96497373, 0.96672504, 0.96532399]),
'test_f1_weighted': array([0.96352096, 0.96455609, 0.96489876, 0.96667345, 0.96525427])}
mean score test accuracy: 0.9650463337699353
mean score test precision weighted: 0.9654334437437194
mean score test recall weighted: 0.9650463337699353
mean score test f1-measure weighted: 0.9649807059388958
Confusion Matrix: [[7704 134]
                        [ 365 6073]]
****Naive-Bayes mean scores TFIDFVECTORIZER****
scores: {'fit_time': array([0.10076237, 0.09514427, 0.09485245, 0.09402418, 0.09432292]),
 score time': array([0.01139355, 0.01068044, 0.01070833, 0.01060581, 0.01093888]),
scote_cime: airay([0.01159355, 0.01060044, 0.011070835, 0.01060081, 0.01093888]),
'test_accuracy': array([0.9772409 , 0.97478109, 0.97688266, 0.9765324 , 0.97618214]),
'test_precision_weighted': array([0.9781468 , 0.97588893, 0.97781698, 0.97749407, 0.97717212]),
'test_recall_weighted': array([0.9772409 , 0.97478109, 0.97688266, 0.9765324 , 0.97618214]),
'test_fl_weighted': array([0.9771774 , 0.9747017 , 0.97681713, 0.97646426, 0.97611174])}
mean score test accuracy: 0.9763238360142656
mean score test precision weighted: 0.9773037810783135
mean score test recall weighted: 0.9763238360142656
mean score test f1-measure weighted: 0.9762544433551351
Confusion Matrix: [[7838
                         [ 338 6100]]
```

CountVectorizer provides a simple way to keep every ingredient as a whole word and keeps 1 if the specific word exists in the recipe else 0, whereas TfidVectorizer calculates term frequency

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(TF) of the ingredients in each recipe without keeping the text of the ingredient as a whole word. For example, CountVectorizer would keep 'jalapenosauce' but TfidfVectorizer would keep 'jalapeno', 'sauce'. CountVectorizer in our case is in binary form, TfidfVectorizer has in each vector the numbers (weights) represent features tf-idf score.

As we can see the TfidVectorizer performs better in all classifiers.

Analysis 2: Compare Classifier metrics VS Clustering metrics (both with CountVectorizer

In the second experiment, we work with the category "moroccan", "filipino" and "british", implementing the above classifiers and comparing the results with those of **agglomerative clustering** and **k-means** that we computed in a previous project on the same dataset (https://github.com/ioannapap/clustering).

The prior difference between classification and clustering is that classification is used in supervised learning technique where predefined labels are assigned to instances by properties and we want to know which class a new object belongs to, on the contrary, clustering is used in unsupervised learning where similar instances are grouped, based on their features or properties.

```
clustering = AgglomerativeClustering(n clusters = 3, linkage='ward').fit(df)
print(np.unique(clustering.labels_))
[0 1 2]
def cluster class mapping(predicted, true labels):
    C = metrics.confusion matrix(predicted, true labels)
   mapping = list(np.argmax(C,axis=1)) #for each row (cluster) find the best,,,→class in the co
nfusion matrix
   mapped kmeans labels = [mapping[l] for l in predicted]
   C2 = metrics.confusion matrix(clustering.labels ,actual)
   return mapped kmeans labels,C2
mapped_agglo_labels,C = cluster_class_mapping(clustering.labels_,actual)
print('Confusion matrix (for Agglomerative): \n' ,C)
def cluster class mapping(predicted, true labels):
    C = metrics.confusion matrix(predicted,true labels)
    mapping = list(np.argmax(C,axis=1)) #for each row (cluster) find the best,, \rightarrow class in the co
nfusion matrix
    mapped kmeans labels = [mapping[l] for l in predicted]
    C2 = metrics.confusion matrix(mapped kmeans labels, true labels)
    return mapped kmeans labels,C2
mapped kmeans labels,C = cluster class mapping(k predicted,actual)
print('Confusion matrix (for k-means): \n' ,C)
****** Agglomerative Clustering ******
                                                  Confusion matrix (for Agglomerative):
Percision:
                         Recall:
                                                   [[ 60 784 191]
                                                   [761 8 1]
[ 0 12 563]]
0.9074233883276631
                         0.8857142857142857
****** K-means Clustering ******
Percision:
                                                  Confusion matrix (for k-means):
                         Recall:
                                                   [[770 7 0]
                                                   [ 51 777 62]
0.9451027664328102
                         0.9411764705882353
                                                   [ 0 20 693]]
****Logistic Regression mean scores****
```

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```
mean score test precision weighted: 0.9311110649318362
mean score test recall weighted: 0.930252100840336
****SVM mean scores****
mean score test accuracy: 0.9315126050420167
mean score test precision weighted: 0.9318336338131683
mean score test recall weighted: 0.9315126050420167
mean score test f1-measure weighted: 0.9315318350559185
****Decision Tree mean scores****
mean score test accuracy: 0.8176470588235294
mean score test precision weighted: 0.8192663317138272
mean score test recall weighted: 0.8176470588235294
****k-NN mean scores****
mean score test accuracy: 0.799579831932773
mean score test precision weighted: 0.8017776971681257
mean score test recall weighted: 0.799579831932773
mean score test f1-measure weighted: 0.7994065502172664
Confusion Matrix: [[651 61 109]
                [ 86 626 92]
[ 43 86 626]]
****Naive-Bayes mean scores***
mean score test accuracy: 0.911344537815126
mean score test precision weighted: 0.9159718744022938
mean score test recall weighted: 0.911344537815126
mean score test f1-measure weighted: 0.9119924610904245
Confusion Matrix: [[744 67 10]
[ 20 759 25]
                [ 14 75 666]]
```

Clustering performs better in all cases as far as confusion-matrix is considered. However, for precision and recall SVM and Naive-Bayes scales better.

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Well, confusion matrix is a performance measurement for machine learning classification problem where output can be two or more classes. It is a table with 4 different combinations of predicted and actual values.

Actual Values

		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
Predicte	Negative (0)	FN	TN

Well...That TP, FP, FN, TN what is all about?

TP stands for True Positive. That means you predicted positive and it's true.

FP stands for False Positive. You predicted positive and it's false.

FN stands for False Negative. You predicted negative and it's false.

TN stands for True Negative. You predicted negative and it's true.

So the conclusion of the confusion matrix is that we want our output to have as many "items" as possible to be in diagonal. For the perfect classifier the outputs are only in the diagonal.

Example: *We want to predict if it is a cat, a dog or a rabbit.*

	Actual Dog	Actual Cat	Actual Rabbit
Classified Dog	23	12	7
Classified Cat	11	29	13
Classified Rabbit	4	10	24