Milestone3_preidct_multilabel_whole_dataset

May 1, 2017

In this python notebook, we use skmultilearn package as it focuses on multilabel classification. We input the processeed data and use the training set to train the model and examine performance metrics for the test set.

0.0.1 Multi-label classification strategy

We will use multi-label classification. Before we discuss which classifier to use (ex. KNN, SVM), we should consdier how we will treat the response variable first.

The "strategies" we used is listed below: 1. Binary Relevence(BR) we seperate each genre into seperate problems (one for each genre). However, this ignore label dependence. Ex. if a movie is tagged as Drama, it is likely that it is also tagged as Action. if a movie is tagged as Horror, it is likely that it is also tagged as Romance. If two classes of a genre (Yes/No) have very uneven sizes in the training set, the classifier will lean toward the class with higher movie number. There is a method called a label correction strategy that can help to improve accuracy For example, if our prediction is [Y_horror, Y_romance, Y_drama]= [1,1,0], which does not really happen in training set. We find another likely matching vector. We may change our prediction to be [1,0,1].

2. Classifier Chains (CC) We seperate each genre into seperate problems, but include previous predictions as predictors. For example, X is our predictor for Y_horror. Next, X, Y_horror are our predictor for Y_romance. However, error may be propagated down the chain.

3. Label Powerset (LP) Instead of having seperate Y_i for each genre i, we will predict only Y. Y has 2^I possible values where I is the number of genre. For example, if Y_horror = 1, Y_romance = 0, Y_drama = 1, Y = [101] However, imbalance of the data can be an issue.

0.0.2 Classifier

For each of the strategy, we will then apply different classifier. 1. KNN 2. SVM

0.0.3 Performance mertic

Please refer to the python notebook "Milestone3_performancemetrics". In short, we will evaluate majorly based on F1 score and Hamming loss.

```
In [1]: import os
        import numpy as np
        import pandas as pd
        import matplotlib
        import matplotlib.pyplot as plt
        from mpl_toolkits.mplot3d import Axes3D
        import matplotlib.cm as cmx
        import matplotlib.colors as colors
        import math
        import seaborn.apionly as sns
        import datetime as dt
```

```
from sklearn.metrics import hamming_loss
from sklearn.metrics import accuracy_score
from sklearn.metrics import f1_score
from sklearn.metrics import precision_score
from sklearn.metrics import jaccard_similarity_score

from skmultilearn.problem_transform import BinaryRelevance, LabelPowerset, ClassifierChain
from sklearn.naive_bayes import GaussianNB
from skmultilearn.ensemble.rakeld import RakelD

from sklearn.model_selection import GridSearchCV
from sklearn.naive_bayes import MultinomialNB

# classifier
from skmultilearn.adapt import MLkNN
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC, LinearSVC

from functools import partial

# cross validation
from sklearn.model_selection import KFold
from sklearn.model_selection import StratifiedKFold

%matplotlib inline
```

In [2]:
```
dir_python_notebook = os.getcwd()
dir_movie_project = os.path.abspath(os.path.join(dir_python_notebook, os.pardir))
dir_data = os.path.join(dir_movie_project, 'project')
```

1 Global variable

In [3]:
```
MODELS = {
    "Gaussian Naive Bayes": GaussianNB(),
    #"Random Forest": RandomForestClassifier(random_state=0),
    #"Extra Trees": ExtraTreesClassifier(n_estimators=100, random_state=0),
    "SVM": SVC(),
    "KNN, k=5": KNeighborsClassifier(n_neighbors=5),
    #"KNN, k=10": KNeighborsClassifier(n_neighbors=10),
}
```

In [4]:
```
STRATEGIES = {
     'Binary Relevance': BinaryRelevance(),
    'Classifier Chain': ClassifierChain(),
    'Label Powerset': LabelPowerset()

}
```

2 Data

2.1 sample

We originall have downloaded the movies with TMDB id from 1 to 300000. 1. many id in between that range actually are not valid (There is no movie for that tmdb id) 2. We only include movies that have data in both TMDB and IMDB. 3. We exclude movies that have more than 50% of features missing. Overall, we have 68186 movies.

2.2 predictior variable

1. We originally downloaded all 51 features from IMDB
2. We removes features that have missing rate > 50% for the samples
3. Some features has list of values, such as cast. As the list is ranked by columns, we convert "cast" to "cast1", "cast2", etc, so each column will only hold 1 value , instead of a list of values.
4. We impute the missing data.
5. We conver categorical variable such as "certificates_R" to relative frequency, so we can apply a lot of methods that may only be suitable for numeric values.
6. We select important features by methods like LASSO and Random Forest. Overall, we have 31 predictor variables.

2.3 response variable

1. We use IMDB genre and convert it to 28 columns. They are binary. Ex. if movies has genre of "Horror" and "Crime", the relevent columns will be 1, else 0.
2. Because 28 genres are too many, we decide to reduce the response variable by clustering with methods like K-mean, etc. We have 7 clusters. We also examine the cluster composition to ensure they make senese. Ex. 1 cluster include only "Horror" and "Thriller". 1 cluster includes "Crime", "Mystery","Film.Noir". Overall, we have 7 response variables.

```
In [5]: filename = dir_data + '//imdb_cluster_result_whole.csv'
        data_df= pd.read_csv(filename)

In [6]: data_df.shape

Out[6]: (68186, 66)

In [7]: data_df.columns

Out[7]: Index([u'certificates_R', u'certificates_PG', u'art.direction_1',
               u'assistant.director_1', u'cinematographer_1', u'costume.department_1',
               u'costume.designer_1', u'countries_1', u'director_1', u'distributors_1',
               u'editor_1', u'languages_1', u'make.up_1', u'miscellaneous.companies_1',
               u'miscellaneous.crew_1', u'original.music_1', u'producer_1',
               u'production.companies_1', u'production.manager_1', u'sound.crew_1',
               u'writer_1', u'special.effects.companies_1', u'cast_1', u'cast_2',
               u'cast_3', u'cast_4', u'runtimes_avg', u'rating', u'imdb_id',
               u'tmdb_id', u'Sci.Fi', u'Crime', u'Romance', u'Animation', u'Music',
               u'Adult', u'Comedy', u'War', u'Horror', u'Film.Noir', u'Western',
               u'News', u'Reality.TV', u'Thriller', u'Adventure', u'Mystery', u'Short',
               u'Talk.Show', u'Drama', u'Action', u'Documentary', u'Musical',
               u'History', u'Family', u'Fantasy', u'Game.Show', u'Sport', u'Biography',
               u'cluster_response', u'cluster_1', u'cluster_2', u'cluster_3',
               u'cluster_4', u'cluster_5', u'cluster_6', u'cluster_7'],
              dtype='object')
```

```
In [8]: X_var= list(data_df.columns.values)
        X_var = X_var[0:28]
        print(len(X_var))
        print(X_var)
```

```
28
['certificates_R', 'certificates_PG', 'art.direction_1', 'assistant.director_1', 'cinematographer_1', 'co
```

```
In [9]: Y_var = list(data_df.columns.values)
        Y_var = Y_var[59:66]
        print(len(Y_var))
        print(Y_var)
```

```
7
['cluster_1', 'cluster_2', 'cluster_3', 'cluster_4', 'cluster_5', 'cluster_6', 'cluster_7']
```

3 Prediction

```
In [10]: def get_metric_data_frame(Y_true_train, y_pred_train,train, model_name, strategy):
             metric_train = {}
             metric_train["micro-f1"] = f1_score(Y_true_train, y_pred_train, average="micro")
             metric_train["weighted-f1"] = f1_score(Y_true_train, y_pred_train, average="weighted")
             metric_train["samples-f1"] = f1_score(Y_true_train, y_pred_train, average="samples")
             metric_train["macro-f1"] = f1_score(Y_true_train, y_pred_train, average="macro")
             metric_train["hamming_loss"] = hamming_loss(Y_true_train, y_pred_train)
             metric_train["subset_accuracy"] = accuracy_score(Y_true_train, y_pred_train)
             metric_train["jaccard"] = jaccard_similarity_score(Y_true_train, y_pred_train)

             metric_test_df_new = pd.DataFrame.from_dict(metric_train, orient='index').transpose()
             metric_test_df_new['model'] = model_name
             metric_test_df_new['strategy'] = strategy
             metric_test_df_new['train_test'] = train

             return metric_test_df_new
```

```
In [11]: def get_predicion_result(X_train, Y_true_train, X_test, Y_true_test, strategy, model, model_nam

             clf = BinaryRelevance(model)
             if (strategy == "Classifier Chain"):
                 clf = ClassifierChain(model)
             if (strategy == "Label Powerset"):
                 clf = LabelPowerset(model)
             # train
             clf.fit(X_train, Y_true_train)

             # predict
             y_pred_train = clf.predict(X_train)
             y_pred_test = clf.predict(X_test)


             metric_df = get_metric_data_frame(Y_true_train, y_pred_train, "train", model_name, strateg
             metric_df  = metric_df.append(get_metric_data_frame(Y_true_test, y_pred_test, "test", model

             return metric_df
```

```
In [12]: def predict(X_train, Y_true_train, X_test, Y_true_test, model_name_list, strategy_list):
             count = 0
             for i in range(len(model_name_list)):
                 model_name = model_name_list[i]
                 model = MODELS[model_name]
                 for strategy in strategy_list:

                     metric_df_new = get_predicion_result(X_train, Y_true_train, X_test, Y_true_test,st
                     if count > 0 :
                         metric_df = metric_df.append(metric_df_new, ignore_index=True)
                     else:
                         metric_df = metric_df_new

                     count = count + 1

             return metric_df
```

3.1 Tuning

We examinf KNN and SVM. To use the prediction methods, plesae add the new model and the optimal parameter in the dictionary MODELS.

3.1.1 Resource

Cross validation example from scikit-multilearn: http://scikit.ml/api/loading.html#cross-validation-and-train-test-splits

Tuning parameter example from scikit-multilearn: http://scikit.ml/api/model_estimation.html#estimating-hyper-parameter-k-for-embedded-classifiers

```
In [13]: train_df = data_df[data_df[u'tmdb_id'] < 100000]
         test_df = data_df[data_df[u'tmdb_id'] >= 100000]
         X_train = train_df[X_var]
         Y_true_train = train_df[Y_var]
         X_test = test_df[X_var]
         Y_true_test = test_df[Y_var]
```

3.2 Tuning for KNN

```
In [14]: # find out what parameters can we tune
         KNeighborsClassifier().get_params().keys()

         # I choose to only tune n_neightbors
```

```
Out[14]: ['n_neighbors',
          'n_jobs',
          'algorithm',
          'metric',
          'metric_params',
          'p',
          'weights',
          'leaf_size']
```

```
In [15]: parameters = {
             'labelset_size': [7],
             'classifier': [BinaryRelevance()],
```

```
            'classifier__classifier': [KNeighborsClassifier()],
            'classifier__classifier__n_neighbors': [1, 9],
        }

        clf = GridSearchCV(RakelD(), parameters, scoring='f1_macro')
        clf.fit(X_train, Y_true_train)

        print clf.best_params_, clf.best_score_
```

```
{'labelset_size': 7, 'classifier__classifier': KNeighborsClassifier(algorithm='auto', leaf_size=30, metri
           metric_params=None, n_jobs=1, n_neighbors=1, p=2,
           weights='uniform'), 'classifier': BinaryRelevance(classifier=KNeighborsClassifier(algorithm=
           metric_params=None, n_jobs=1, n_neighbors=1, p=2,
           weights='uniform'),
        require_dense=[True, True]), 'classifier__classifier__n_neighbors': 1} 0.365419276444
```

```
In [16]: parameters = {
            'labelset_size': [7],
            'classifier': [ClassifierChain()],
            'classifier__classifier': [KNeighborsClassifier()],
            'classifier__classifier__n_neighbors': [1, 9],
        }

        clf = GridSearchCV(RakelD(), parameters, scoring='f1_macro')
        clf.fit(X_train, Y_true_train)

        print clf.best_params_, clf.best_score_
```

```
{'labelset_size': 7, 'classifier__classifier': KNeighborsClassifier(algorithm='auto', leaf_size=30, metri
           metric_params=None, n_jobs=1, n_neighbors=1, p=2,
           weights='uniform'), 'classifier': ClassifierChain(classifier=KNeighborsClassifier(algorithm=
           metric_params=None, n_jobs=1, n_neighbors=1, p=2,
           weights='uniform'),
        require_dense=[True, True]), 'classifier__classifier__n_neighbors': 1} 0.365419276444
```

```
In [17]: parameters = {
            'labelset_size': [7],
            'classifier': [LabelPowerset()],#[LabelPowerset(), BinaryRelevance()],
            'classifier__classifier': [KNeighborsClassifier()],
            'classifier__classifier__n_neighbors': [1, 9],
        }

        clf = GridSearchCV(RakelD(), parameters, scoring='f1_macro')
        clf.fit(X_train, Y_true_train)

        print clf.best_params_, clf.best_score_
```

```
{'labelset_size': 7, 'classifier__classifier': KNeighborsClassifier(algorithm='auto', leaf_size=30, metri
           metric_params=None, n_jobs=1, n_neighbors=1, p=2,
           weights='uniform'), 'classifier': LabelPowerset(classifier=KNeighborsClassifier(algorithm='au
           metric_params=None, n_jobs=1, n_neighbors=1, p=2,
           weights='uniform'),
       require_dense=[True, True]), 'classifier__classifier__n_neighbors': 1} 0.365419276444
```

3.3 Tuning for SVM

A smaller dataset was used here for tuning

```
In [18]: SVC().get_params().keys()
```

```
Out[18]: ['kernel',
          'C',
          'verbose',
          'probability',
          'degree',
          'shrinking',
          'max_iter',
          'decision_function_shape',
          'random_state',
          'tol',
          'cache_size',
          'coef0',
          'gamma',
          'class_weight']
```

```
In [19]: df_new = data_df[data_df[u'tmdb_id'] < 10000]
         X_train1 = df_new[X_var]
         Y_true_train1 = df_new[Y_var]
```

```
In [20]: parameters = {
             'labelset_size': [7],
             'classifier': [BinaryRelevance()],
             'classifier__classifier': [SVC()],
             'classifier__classifier__C': [1, 10, 100],
             'classifier__classifier__gamma': [0.1, 0.01, 0.001]
         }

         clf = GridSearchCV(RakelD(), parameters, scoring='f1_macro')
         clf.fit(X_train1, Y_true_train1)

         print clf.best_params_, clf.best_score_
```

```
/Users/aixu/anaconda/lib/python2.7/site-packages/sklearn/metrics/classification.py:1113: UndefinedMetri
  'precision', 'predicted', average, warn_for)

{'classifier__classifier__gamma': 0.1, 'labelset_size': 7, 'classifier__classifier': SVC(C=100, cache_size
  decision_function_shape=None, degree=3, gamma=0.1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False), 'classifier': BinaryRelevance(classifier=SVC(C=100, cache_size=200, class_w
  decision_function_shape=None, degree=3, gamma=0.1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False),
        require_dense=[True, True]), 'classifier__classifier__C': 100} 0.369298212185
```

```
In [21]: parameters = {
             'labelset_size': [7],
             'classifier': [ClassifierChain()],
             'classifier__classifier': [SVC()],
             'classifier__classifier__C': [1, 10, 100],
             'classifier__classifier__gamma': [0.1, 0.01, 0.001]
         }

         clf = GridSearchCV(RakelD(), parameters, scoring='f1_macro')
```

```
        clf.fit(X_train1, Y_true_train1)

        print clf.best_params_, clf.best_score_
```

```
{'classifier__classifier__gamma': 0.1, 'labelset_size': 7, 'classifier__classifier': SVC(C=100, cache_size
  decision_function_shape=None, degree=3, gamma=0.1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False), 'classifier': ClassifierChain(classifier=SVC(C=100, cache_size=200, class_w
  decision_function_shape=None, degree=3, gamma=0.1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False),
        require_dense=[True, True]), 'classifier__classifier__C': 100} 0.374383667391
```

```
In [22]: parameters = {
             'labelset_size': [7],
             'classifier': [LabelPowerset()],
             'classifier__classifier': [SVC()],
             'classifier__classifier__C': [1, 10, 100],
             'classifier__classifier__gamma': [0.1, 0.01, 0.001]
         }

         clf = GridSearchCV(RakelD(), parameters, scoring='f1_macro')
         clf.fit(X_train1, Y_true_train1)

         print clf.best_params_, clf.best_score_
```

```
{'classifier__classifier__gamma': 0.1, 'labelset_size': 7, 'classifier__classifier': SVC(C=100, cache_size
  decision_function_shape=None, degree=3, gamma=0.1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False), 'classifier': LabelPowerset(classifier=SVC(C=100, cache_size=200, class_wei
  decision_function_shape=None, degree=3, gamma=0.1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False),
       require_dense=[True, True]), 'classifier__classifier__C': 100} 0.39160233552
```

```
In [23]: # After tuning, we input the variable below

         MODELS = {
             #"Gaussian Naive Bayes": GaussianNB(),
             #"Random Forest": RandomForestClassifier(random_state=0),
             #"Extra Trees": ExtraTreesClassifier(n_estimators=100, random_state=0),
             "SVM C=100 gamma=0.1": SVC(C=100, gamma=0.1),
             "KNN k=1": KNeighborsClassifier(n_neighbors=1)
         }
```

4 Cross-validation

We tried both traditional k fold and stratified k fold.

```
In [24]: def cross_validate_by_kfold(data_df, X_var, Y_var, n_split):
             count = 0
             # remember to set n_splits and shuffle!
             kf = KFold(n_splits=n_split, random_state=None, shuffle= True)

             X = data_df[X_var]
```

```
    Y = data_df[Y_var]

    for train_index, test_index in kf.split(X, Y):
        X_train = X.iloc[train_index]
        Y_true_train = Y.iloc[train_index]

        X_test = X.iloc[test_index]
        Y_true_test = Y.iloc[test_index]

        model_name_list = MODELS.keys()

        strategy_list = STRATEGIES.keys()

        metric_df_new = predict(X_train, Y_true_train, X_test, Y_true_test, model_name_list, s

        if count == 0 :
            metric_df = metric_df_new
        else:
            metric_df = metric_df.append(metric_df_new, ignore_index=True)
        count = count + 1

    metric_grouped_df = metric_df.groupby(['model','strategy','train_test']).mean().reset_inde

    return metric_grouped_df
```

In [25]:
```
def cross_validate_by_stratifiedkfold(data_df, X_var, Y_var, n_split):
    count = 0

    strategy_list = STRATEGIES.keys()

    for strategy in strategy_list:

        sc = STRATEGIES[strategy]

        # remember to set n_splits and shuffle!
        kf = StratifiedKFold(n_splits=n_split, random_state=None, shuffle=True)

        X = data_df[X_var]
        Y = data_df[Y_var]


        for train_index, test_index in kf.split(X, sc.transform(Y)):

            X_train = X.iloc[train_index]
            Y_true_train = Y.iloc[train_index]

            X_test = X.iloc[test_index]
            Y_true_test = Y.iloc[test_index]

            model_name_list = MODELS.keys()

            #strategy_list = STRATEGIES.keys()
            strategy_list = [strategy]
```

```
                metric_df_new = predict(X_train, Y_true_train, X_test, Y_true_test, model_name_lis

                if count == 0 :
                    metric_df = metric_df_new
                else:
                    metric_df = metric_df.append(metric_df_new, ignore_index=True)

                count = count + 1

        metric_grouped_df = metric_df.groupby(['model','strategy','train_test']).mean().reset_inde

        return metric_grouped_df
```

In [26]:
```
# test with a smaller data set to ensure the method works
data_df_new = data_df[data_df[u'tmdb_id'] < 10000]
count = 0
# remember to set n_splits and shuffle!
n_split=5
kf = KFold(n_splits=n_split, random_state=None, shuffle= True)

X = data_df_new[X_var]
Y = data_df_new[Y_var]

for train_index, test_index in kf.split(X, Y):
    X_train = X.iloc[train_index]
    Y_true_train = Y.iloc[train_index]

    X_test = X.iloc[test_index]
    Y_true_test = Y.iloc[test_index]

    model_name_list = MODELS.keys()

    strategy_list = STRATEGIES.keys()

    metric_df_new = predict(X_train, Y_true_train, X_test, Y_true_test, model_name_list, strat

    if count == 0 :
        metric_df = metric_df_new
    else:
        metric_df = metric_df.append(metric_df_new, ignore_index=True)
    count = count + 1

metric_grouped_df = metric_df.groupby(['model','strategy','train_test']).mean().reset_index()
metric_grouped_df
```

```
/Users/aixu/anaconda/lib/python2.7/site-packages/sklearn/metrics/classification.py:1113: UndefinedMetri
  'precision', 'predicted', average, warn_for)
```

Out[26]:

	model	strategy	train_test	micro-f1	jaccard \
0	KNN k=1	Binary Relevance	test	0.504140	0.385477
1	KNN k=1	Binary Relevance	train	1.000000	1.000000
2	KNN k=1	Classifier Chain	test	0.504140	0.385477
3	KNN k=1	Classifier Chain	train	1.000000	1.000000
4	KNN k=1	Label Powerset	test	0.504140	0.385477
5	KNN k=1	Label Powerset	train	1.000000	1.000000

```
6   SVM C=100 gamma=0.1  Binary Relevance       test  0.543212  0.436472
7   SVM C=100 gamma=0.1  Binary Relevance      train  0.762694  0.677212
8   SVM C=100 gamma=0.1  Classifier Chain       test  0.531399  0.423879
9   SVM C=100 gamma=0.1  Classifier Chain      train  0.770996  0.711751
10  SVM C=100 gamma=0.1    Label Powerset       test  0.519697  0.413682
11  SVM C=100 gamma=0.1    Label Powerset      train  0.872640  0.839641

    macro-f1  samples-f1  subset_accuracy  weighted-f1  hamming_loss
0   0.396838    0.496153         0.095512     0.504150      0.323741
1   1.000000    1.000000         1.000000     1.000000      0.000000
2   0.396838    0.496153         0.095512     0.504150      0.323741
3   1.000000    1.000000         1.000000     1.000000      0.000000
4   0.396838    0.496153         0.095512     0.504150      0.323741
5   1.000000    1.000000         1.000000     1.000000      0.000000
6   0.376016    0.548048         0.142920     0.504413      0.268336
7   0.687928    0.755285         0.435129     0.743124      0.139950
8   0.407582    0.532357         0.137605     0.518993      0.293114
9   0.724162    0.770324         0.547178     0.765250      0.143443
10  0.394011    0.522172         0.130899     0.509420      0.304546
11  0.853333    0.870807         0.755666     0.871068      0.081199
```

5 Get performance metrics

We decided to use **weighted-f1** and **hamming_loss** as our final performance metrics We also calculated accuracy (sub-set accuracy) here as a reference.

In [27]:
```python
def get_metric_data_frame(Y_true_train, y_pred_train,train, model_name, strategy):
    metric_train = {}

    metric_train["weighted-f1"] = f1_score(Y_true_train, y_pred_train, average="weighted")
    metric_train["hamming_loss"] = hamming_loss(Y_true_train, y_pred_train)
    metric_train["subset_accuracy"] = accuracy_score(Y_true_train, y_pred_train)

    metric_test_df_new = pd.DataFrame.from_dict(metric_train, orient='index').transpose()
    metric_test_df_new['model'] = model_name
    metric_test_df_new['strategy'] = strategy
    metric_test_df_new['train_test'] = train

    return metric_test_df_new
```

In [29]:
```python
# test
n_split = 5
metric_df_kfold  = cross_validate_by_kfold(data_df, X_var, Y_var, n_split)
```

In [30]:
```python
metric_df_stratifiedkfold  = cross_validate_by_kfold(data_df, X_var, Y_var, n_split)
```

6 Visualization on performance

In [33]:
```python
def plot_metric_for_strategy(train_test, strategy, metric):
    title = metric + " for " + strategy
    metric_plot_df = metric_df[(metric_df['strategy']== strategy) & (metric_df['train_test']==
    fig, ax = plt.subplots(1, 1, figsize=(8,4))
    ax = sns.barplot(x="model", y=metric, data=metric_plot_df)
    xt = plt.xticks(rotation=45)
```

```
        ax.set_title(title)
        plt.show()
```

In [34]:
```
metric_df = metric_df_stratifiedkfold
```

In [42]:
```
metric_df
```

Out[42]:
```
                   model          strategy train_test  weighted-f1  \
0                KNN k=1  Binary Relevance       test     0.505841
1                KNN k=1  Binary Relevance      train     1.000000
2                KNN k=1  Classifier Chain       test     0.505841
3                KNN k=1  Classifier Chain      train     1.000000
4                KNN k=1    Label Powerset       test     0.505841
5                KNN k=1    Label Powerset      train     1.000000
6    SVM C=100 gamma=0.1  Binary Relevance       test     0.495819
7    SVM C=100 gamma=0.1  Binary Relevance      train     0.651347
8    SVM C=100 gamma=0.1  Classifier Chain       test     0.522307
9    SVM C=100 gamma=0.1  Classifier Chain      train     0.686180
10   SVM C=100 gamma=0.1    Label Powerset       test     0.508691
11   SVM C=100 gamma=0.1    Label Powerset      train     0.789247

    hamming_loss  subset_accuracy
0       0.317161         0.101315
1       0.000000         1.000000
2       0.317161         0.101315
3       0.000000         1.000000
4       0.317161         0.101315
5       0.000000         1.000000
6       0.245274         0.165265
7       0.169993         0.330113
8       0.264562         0.163188
9       0.174787         0.410473
10      0.279473         0.160818
11      0.122333         0.608135
```

In [44]:
```
metric_plot_df = metric_df[(metric_df['strategy']== 'Binary Relevance') & (metric_df['train_te
metric_plot_df
```

Out[44]:
```
                  model          strategy train_test  weighted-f1  \
0               KNN k=1  Binary Relevance       test     0.505841
6   SVM C=100 gamma=0.1  Binary Relevance       test     0.495819

   hamming_loss  subset_accuracy
0      0.317161         0.101315
6      0.245274         0.165265
```

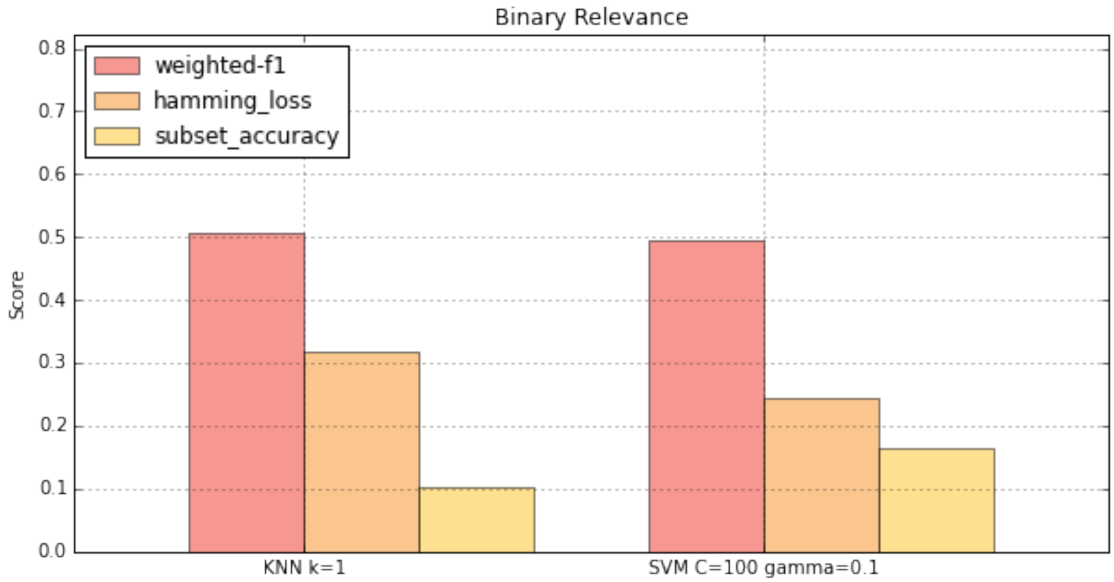
1. Compare Metrics (Weighted-F1, Hamming_Loss)

In [63]:
```
df=metric_df
def plot_comparison(strategy, metric1, metric2, metric3):
    metric_plot_df = df[(df['strategy']== strategy) & (df['train_test']== 'test')]
    # Setting the positions and width for the bars
    pos = list(range(len(metric_plot_df['model'])))
    width = 0.25
    # Plotting the bars
```

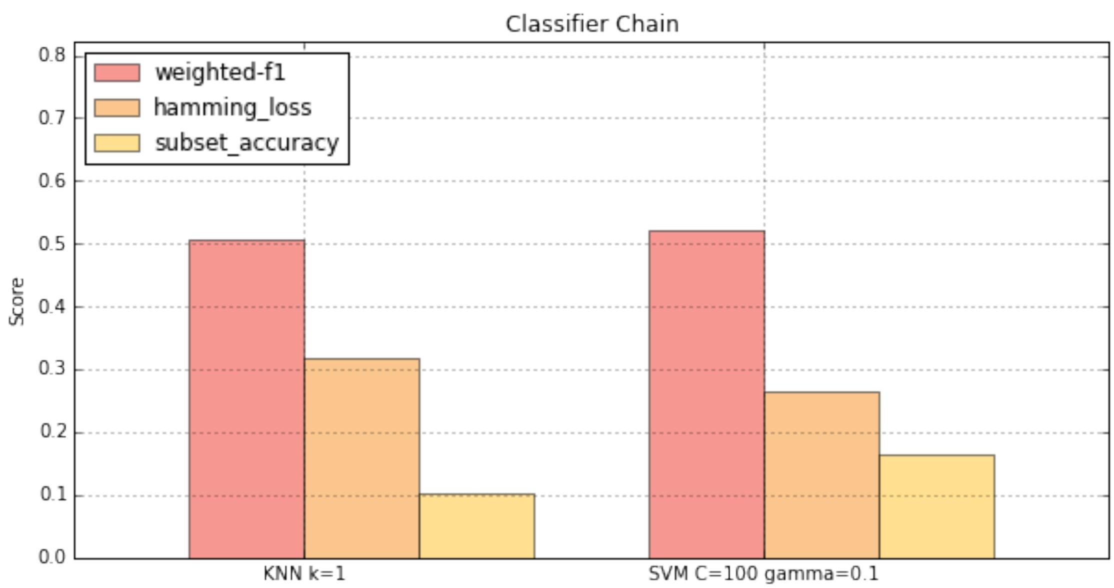
```
fig, ax = plt.subplots(figsize=(10,5))
# Create a bar with pre_score data,
# in position pos,
plt.bar(pos,

    metric_plot_df[metric1],
    # of width
    width,
    # with alpha 0.5
    alpha=0.5,
    # with color
    color='#EE3224',

    label='KNN k=1'
       )
# Create a bar with mid_score data,
# in position pos + some width buffer,
plt.bar([p + width for p in pos],

    metric_plot_df[metric2],
    # of width
    width,
    # with alpha 0.5
    alpha=0.5,
    # with color
    color='#F78F1E',
    # with label the second value in model
    label='SVM C=100 gamma=0.1'
       )

plt.bar([p + 2*width for p in pos],

    metric_plot_df[metric3],
    # of width
    width,
    # with alpha 0.5
    alpha=0.5,
    # with color
    color='#FFC222',
    # with label the third value in first_name
    #label=metric_plot_df['first_name'][2]
       )

# Set the y axis label
ax.set_ylabel('Score')

# Set the chart's title
ax.set_title(strategy)

# Set the position of the x ticks
ax.set_xticks([p +  width for p in pos])

# Set the labels for the x ticks
ax.set_xticklabels(metric_plot_df['model'].values)
```

```
    # Setting the x-axis and y-axis limits
    plt.xlim(min(pos)-width, max(pos)+width*4)
    plt.ylim([0, max(metric_plot_df[metric1] + metric_plot_df[metric2])])

    # Adding the legend and showing the plot
    plt.legend([metric1, metric2, metric3], loc='upper left')
    plt.grid()
    plt.show()
```

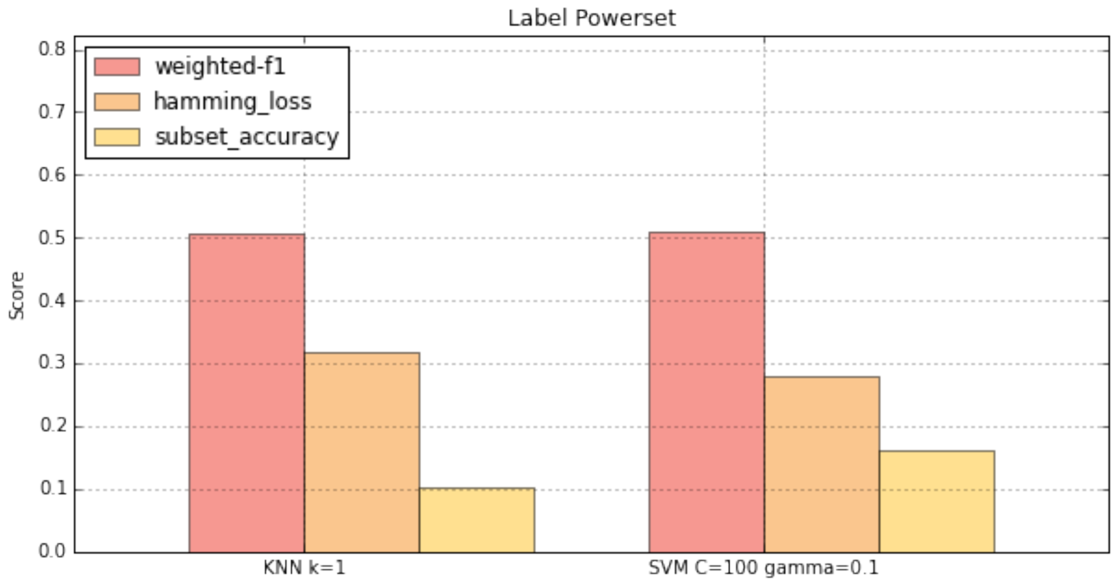
```
In [50]: plot_comparison('Binary Relevance', 'weighted-f1','hamming_loss','subset_accuracy')
```




```
In [51]: plot_comparison('Classifier Chain','weighted-f1','hamming_loss','subset_accuracy')
```

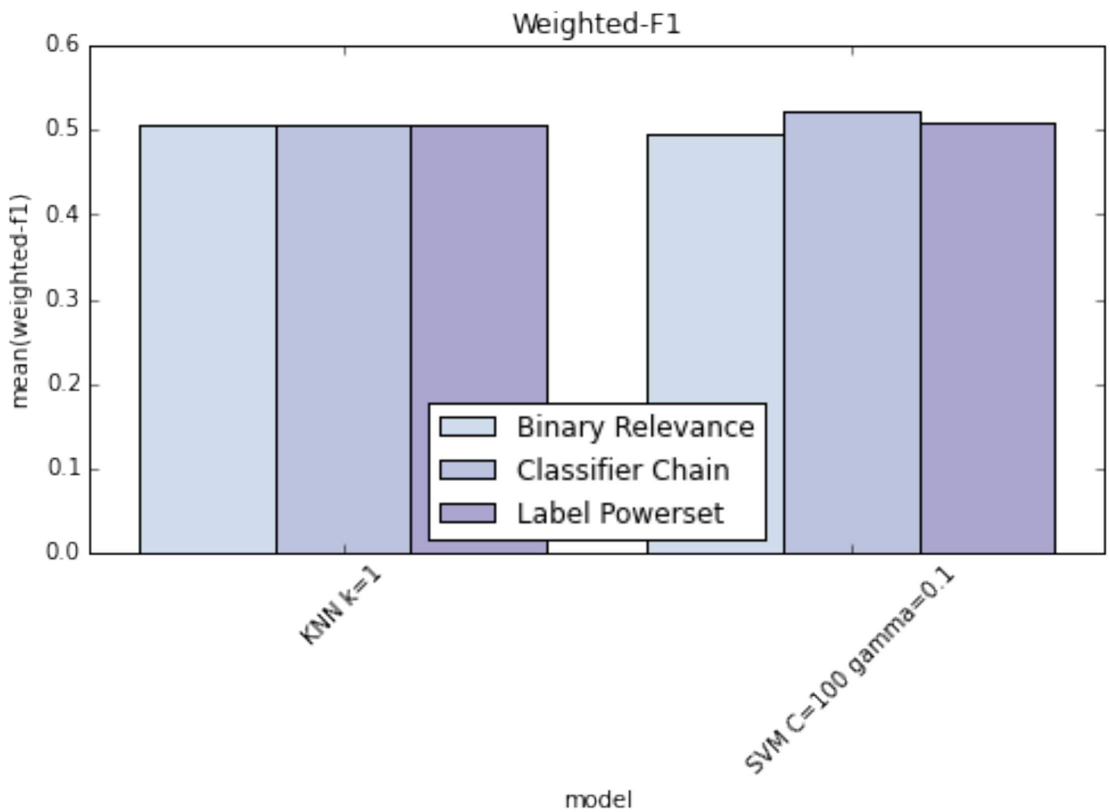


```
In [52]: plot_comparison('Label Powerset','weighted-f1','hamming_loss','subset_accuracy')
```

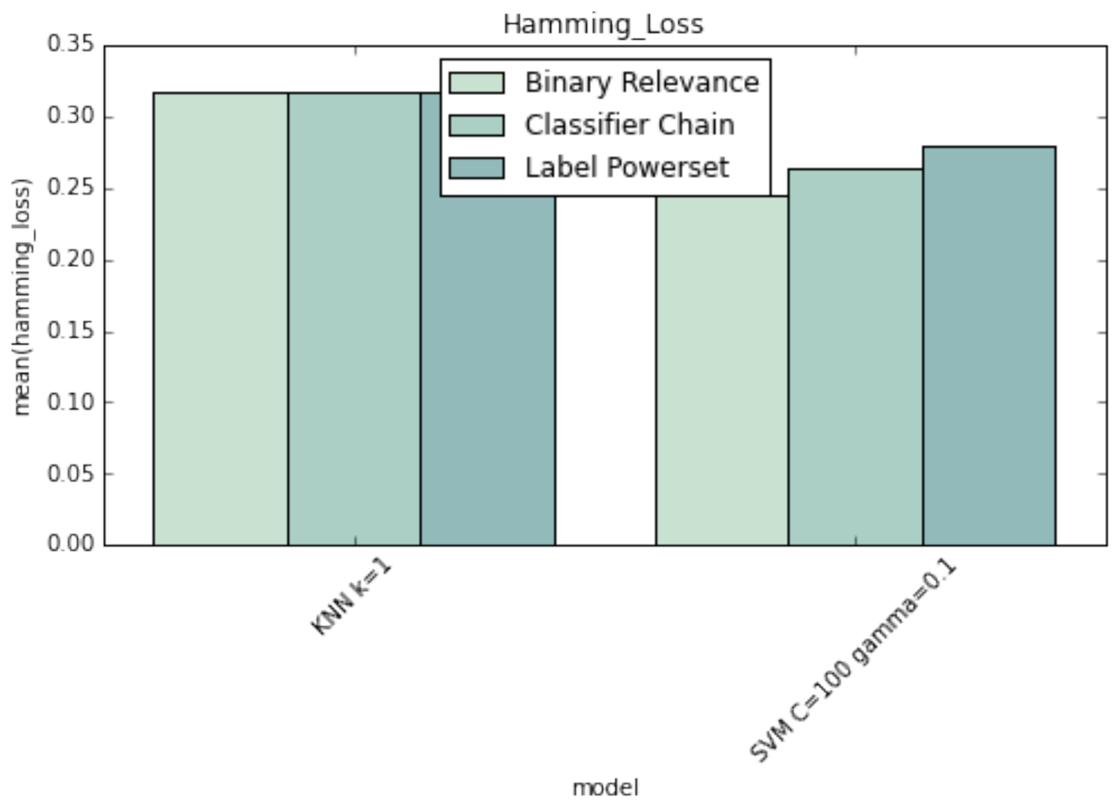


2. Compare Strategies (Binary Relevance, Classifier Chain, Label Powerset)

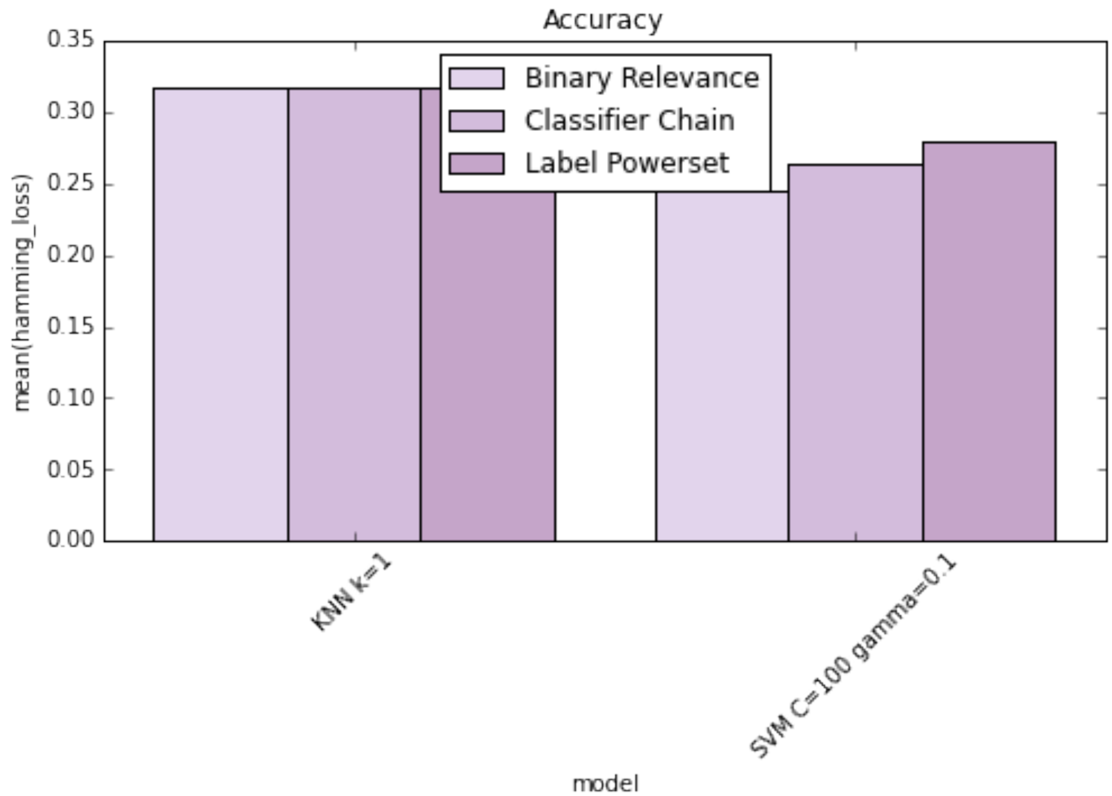
```
In [53]: metric_plot_df = metric_df[(metric_df['train_test']== 'test')]
         fig, ax = plt.subplots(1, 1, figsize=(8,4))
         sns.set_palette(sns.cubehelix_palette(8,start=1, rot=-.5))
         ax = sns.barplot(x="model", y="weighted-f1", hue="strategy", data=metric_plot_df)
         xt = plt.xticks(rotation=45)
         ax.set_title("Weighted-F1")
         plt.legend(loc='best')
         plt.show()
```




```
In [54]: metric_plot_df = metric_df[(metric_df['train_test']== 'test')]
         fig, ax = plt.subplots(1, 1, figsize=(8,4))
         sns.set_palette(sns.cubehelix_palette(10,start=1, rot=-.75))
         ax = sns.barplot(x="model", y="hamming_loss", hue="strategy", data=metric_plot_df)
         xt = plt.xticks(rotation=45)
         ax.set_title("Hamming_Loss")
         plt.legend(loc='best')
         plt.show()
```

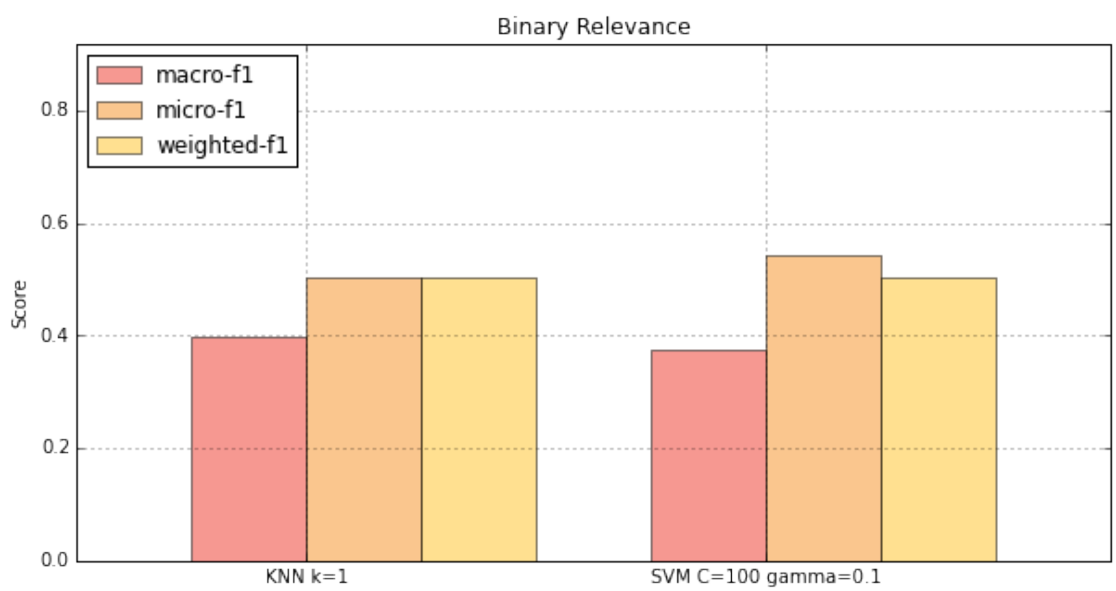



```
In [60]: metric_plot_df = metric_df[(metric_df['train_test']== 'test')]
         fig, ax = plt.subplots(1, 1, figsize=(8,4))
         sns.set_palette(sns.cubehelix_palette(10,start=1, rot=-.3))
         ax = sns.barplot(x="model", y="hamming_loss", hue="strategy", data=metric_plot_df)
         xt = plt.xticks(rotation=45)
         ax.set_title("Accuracy")
         plt.legend(loc='best')
         plt.show()
```

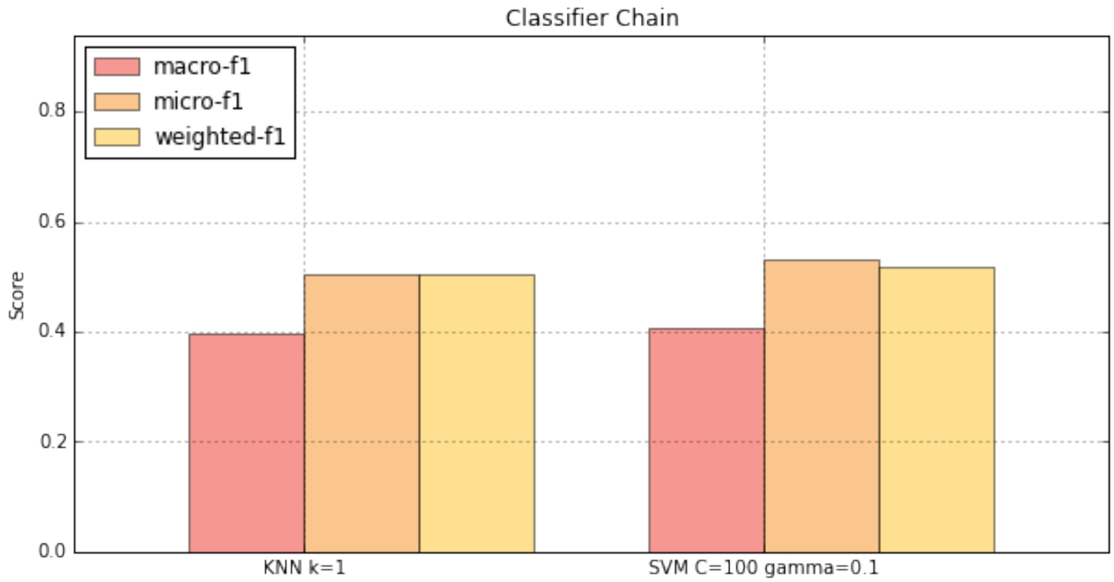


3. Compare Macro f1 vs Micro f1

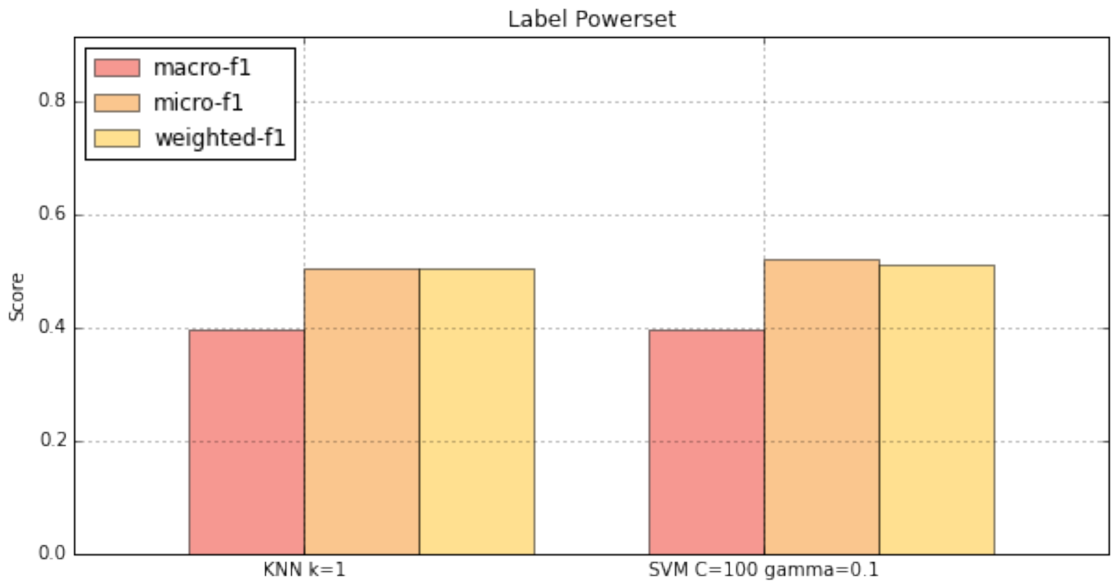
```
In [66]: df=metric_grouped_df
         plot_comparison('Binary Relevance', 'macro-f1','micro-f1','weighted-f1')
```



```
In [67]: plot_comparison('Classifier Chain', 'macro-f1','micro-f1','weighted-f1')
```




```
In [68]: plot_comparison('Label Powerset', 'macro-f1','micro-f1','weighted-f1')
```



7 Results and Discussion

7.1 Goal

1. We examine the performance metric for the test set among various classifiers.

    - For hamming loss, the smaller the value , the smaller the difference between predicted and true labels.
    - For F1 score, the larger the value , the smaller the difference between predicted and true labels. We will focus on weighted F1 score for now.

2. We examine the performance metric for each strategy :Binary Relevance,Classifier Chain,Label Powerset.

3. We will look into the performance metric for labels with more movies vs labels with fewer moviews.

    - We can examine the difference between F1 score for macro average and micro average. If the micro-average result is significantly lower than the macro-average one, it means that we have some gross misclassification in the most populated labels, whereas our smaller labels are probably correctly classified.

4. We examine if cross-validation by kfold has similiar result as by stratified kfold

    - k-folding may lead to severe problems with label combination representability across folds, thus if the data exhibits a strong label co-occurrence structure, using a label-combination based stratified k-fold will be better.

7.2 1. Classifier with the best metric

After comparing KNN and SVM based on weighted-f1 and hamming_loss, we found out the **SVM** has lower hamming_loss scores for all 3 strategies, and weighted-f1 for both classifier are similiar. The performances of KNN and SVM does not differ much. Generally, **SVM** is better. As we only tuned limited set of parameters for SVM here, we may need to re-do the parameter tuning on whole dataset to get more accurate results.

7.3 2. Strategy with the best metric

For **KNN**, three strategies have same performance for both weighted-f1 and hamming_loss metrics For **SVM**, Binary Relevance has lowest hamming_loss score and Classifier Chain has highest weighted-f1 score. In general, **Binary Relevance** and **Classifier Chain** have better performance on our models.

7.4 3. If the best method we pick favor any label of size differences

As can be seen in the plots above, macro F1 score is slighly lower than micro F1 score (mean difference 0.1). It indicates that we may fit more poorly in clusters which have fewer movies. We have already tried our best to address the problem of uneven numbers by using stratified k-fold cross-validation. Since the difference between micro and macro F1s is not very large, we can assume all the clusters are correctly classified.