The notebook requires the python files we submitted.

Data Acquisition

We acquire data from TMDB, or The Movie DataBase, which is an open source version of IMDB, by using its API. Specifically, we do the following:

1. Get list of movie genres.
2. Obtain information of all movies in TMDB, including genres, overviews, poster paths, and etc.
3. Download posters for the movies in the preprocessed list of movies, and resize them into 224 X 224 (pixels).

In [1]:

```
import warnings
warnings.filterwarnings('ignore')

if False:

    import time
    import requests
    from collections import OrderedDict

    import tmdbsimple as tmdb # https://www.themoviedb.org/documentati
on/api
    tmdb.API_KEY = ''
    import imdb

    import pickle

    class IO:
        def __init__(self, file_name):
            self.file_name = file_name

        def to_pickle(self, obj):
            with open(self.file_name, 'wb') as output:
                pickle.dump(obj, output, protocol=pickle.HIGHEST_PROTO
COL)

        def read_pickle(self):
            with open(self.file_name, 'rb') as input_:
                obj = pickle.load(input_)
            return obj

    class CountRequest:
        def __init__(self, limit=40, stop=10):
            self.limit = limit
            self.stop = stop
            self.count = 0

        def add(self):
            self.count += 1
```

```
            if self.count % self.limit == 0:
                print('Sleep {} seconds...'.format(self.stop))
                time.sleep(self.stop)
            return self

    data_folder = '../data/'

    # Get list of genres
    tmdb_genres = tmdb.Genres().movie_list()
    cr.add()
    old_ids = []
    tmdb_genres_list = []
    for g in tmdb_genres['genres']:
        old_ids.append(g['id'])
        tmdb_genres_list.append(g['name'])
    old_id2new_id = {_i:i for i, _i in enumerate(old_ids)}
    IO(data_folder + 'tmdb_genres_list.pkl').to_pickle(tmdb_genres_lis
t)

    # Get information of all movies in TMDB
    years = [y for y in range(1880, 2030)]
    tmdb_all = []

    for year in years:
        discover = tmdb.Discover().movie(year=year)
        cr.add()
        #print(year, discover['total_pages'], discover['total_result
s'])
        for page in range(1, min(discover['total_pages']+1, 1001)):
            tmdb_all.extend(tmdb.Discover().movie(year=year, page=page
)['results'])
            cr.add()

    for m in tmdb_all:
        m['genre_ids'] = [old_id2new_id[i] for i in m['genre_ids']]

    IO(data_folder + 'tmdb_all.pkl').to_pickle(tmdb_all)

    # Download posters
    import requests
    poster_folder = '../data/posters/'

    def get_poster(moive_dict):
        url = 'http://image.tmdb.org/t/p/original' + moive_dict['poste
r_path']
        return requests.get(url).content

    tmdb_posters = []

    for i, movie in enumerate(data):
        img = get_poster(movie)
        with open(poster_folder + str(i) + '.jpg', 'wb') as f:
            f.write(img)
        tmdb_posters.append(movie)
        #print(i, movie['title'])
        time.sleep(0.1)
```

```
    IO(data_folder + 'tmdb_posters.pkl').to_pickle(tmdb_posters)
```

Preprocessing

First we need to preprocess our data. For details see common.py. The following code assumes tmdb_posters.pkl in ../data folder and glove.6B.300d.txt in ../local/glove. Results are stored in /tmp, and after that they should be moved to ../local folder.

In [2]:

```
import pickle
import numpy as np
from common import Data, Split, Batches, encode_y, Vocab

if False:
    # load pickled data
    data_file = "../data/tmdb_posters.pkl"
    data = pickle.load(open(data_file, 'rb'))


    # get overviews from data
    OVERVIEWS = Data(np.array([d['overview'] for d in data]))
    # get title from data
    TITLES = Data(np.array([d['title'] for d in data]))

    OVERVIEWS.save("/tmp/overviews.pkl")
    TITLES.save("/tmp/titles.pkl")

    # get genres, encode as 'one'-hot vectors
    GENRES = Data(encode_y(np.array([d['genre_ids'] for d in data])))
    GENRES.save("/tmp/genres.pkl")

    # create train-val-test split
    train, val, test = OVERVIEWS.create_splits(0.8,0.1)
    train.save("/tmp/train.pkl")
    val.save("/tmp/val.pkl")
    test.save("/tmp/test.pkl")

    # create vocab, this is to support fine-tuning of embeddings (othe
rwise don't call add_sentences)
    # during this step, all punctuations are removed and all words are
 converted to lower cases.
    vocab = Vocab()
    vocab.initialize_glove("../local/glove/glove.6B.300d.txt")
    vocab.add_sentences(train.get_data(OVERVIEWS))
    vocab.add_sentences(train.get_data(TITLES))
    vocab.save("/tmp/vocab.pkl")

    # create embedding layer, for now we freeze the embedding layer.
 (default is freeze=True)
    embedding = vocab.create_pytorch_embeddings()
    torch.save(embedding, "/tmp/embedding.pth")

    # encode data as indices
    OVERVIEWS_ENCODED = Data(vocab.encode_sentences(OVERVIEWS.data))
    TITLES_ENCODED = Data(vocab.encode_sentences(TITLES.data))

    OVERVIEWS_ENCODED.save("/tmp/overviews_encoded.pkl")
    TITLES_ENCODED.save("/tmp/titles_encoded.pkl")

    del OVERVIEWS_ENCODED, TITLES_ENCODED, vocab, embedding, train, va
l, test, GENRES, TITLES, OVERVIEWS, data, data_file
```

In [3]:
```
# load saved preprocessed data
from common import load_data, load_split
GENRES = load_data("../local/genres.pkl")
train = load_split("../local/train.pkl")
val = load_split("../local/val.pkl")
test = load_split("../local/test.pkl")
OVERVIEWS = load_data("../local/overviews_encoded.pkl")
OVERVIEWS_ENCODED = OVERVIEWS

from sklearn.metrics import f1_score

def report(Y_true, Y_pred):
    print("acc:", np.mean([np.mean(Y_true[:,i] == Y_pred[:,i]) for i i
n range(19)]), "\tf1:",f1_score(Y_true, Y_pred, average="micro"))
```

EDA

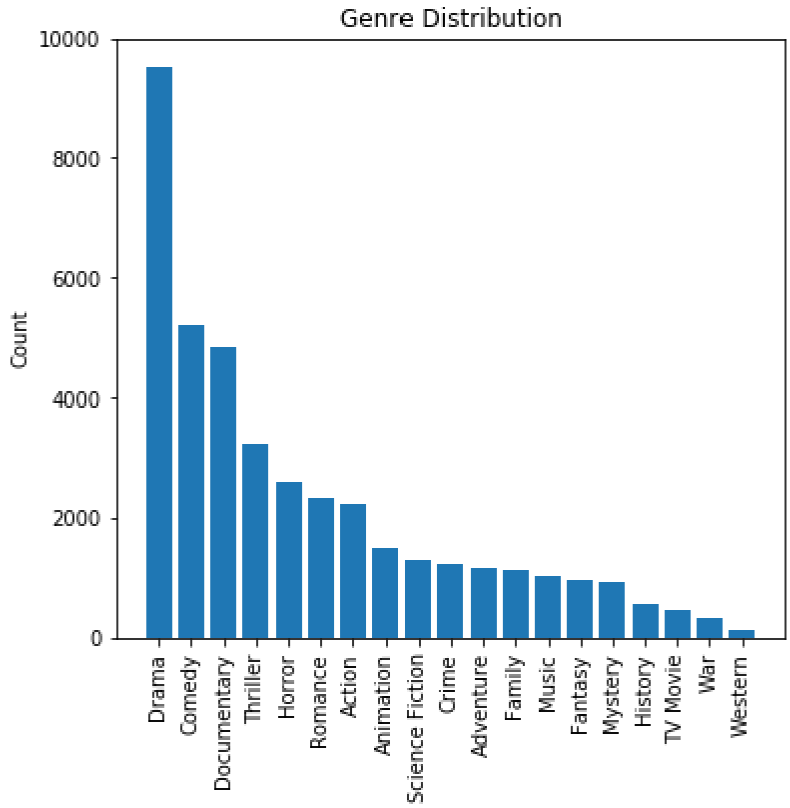
In [4]:
```
import sys
sys.path.append('../')
from modules import IO
import numpy as np
import itertools
import seaborn as sns
import matplotlib.pyplot as plt
color = sns.color_palette("hls", 19)
%matplotlib inline
```

In [5]:
```
data_folder = '../../data/'
output_folder = '../../output/'
tmdb_genres_list = IO(data_folder + 'tmdb_genres_list.pkl').read_pickl
e()
movies = IO(data_folder + 'tmdb_posters.pkl').read_pickle()
```

In [6]:
```
tmdb_all = movies
print(len(tmdb_all))

tmdb_all_genres_count = np.zeros(len(tmdb_genres_list), dtype=int)
tmdb_overview_len = []

for m in tmdb_all:
    for i in m['genre_ids']:
        tmdb_all_genres_count[i] += 1
    tmdb_overview_len.append(len(m['overview'].split(' ')))

tmdb_overview_len = np.array(tmdb_overview_len)
```

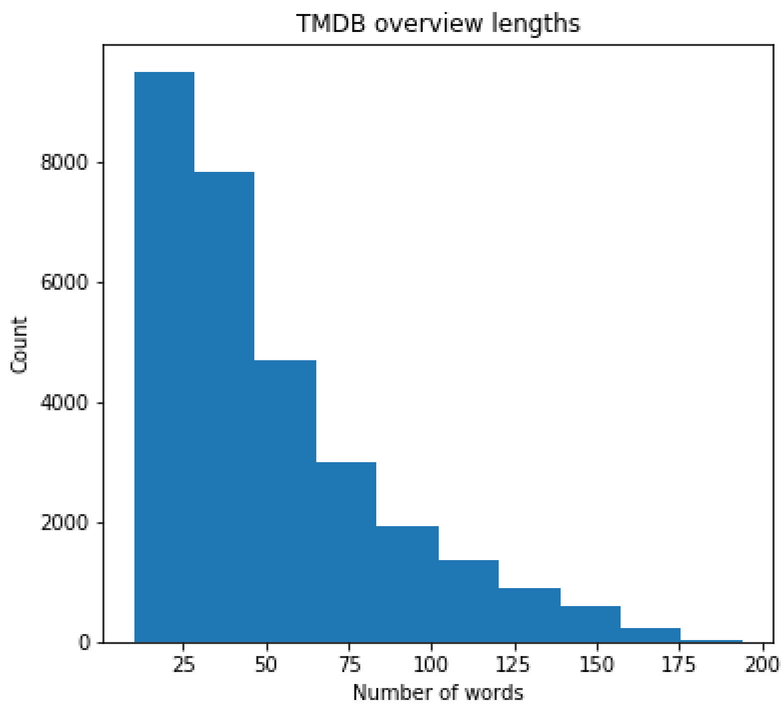
```
30000
```

In [7]:
```
plt.figure(figsize=(6, 5.5))

plt.bar(range(len(tmdb_all_genres_count)), tmdb_all_genres_count[np.ar
gsort(tmdb_all_genres_count)[::-1]]);
plt.xticks(range(len(tmdb_all_genres_count)), np.array(tmdb_genres_lis
t)[np.argsort(tmdb_all_genres_count)[::-1]], \
           rotation=90);
plt.ylabel('Count');
plt.title('Genre Distribution');
#plt.savefig(output_folder + 'eda02.png', bbox_inches='tight');
```



In [8]:
```
plt.figure(figsize=(6, 5.5))
plt.hist(tmdb_overview_len);
plt.xlabel('Number of words');
plt.ylabel('Count');
plt.title('TMDB overview lengths');
#plt.savefig(output_folder + 'eda03.png', bbox_inches='tight');

print('The number of movie overviews with no less than 20 words: {}'.f
ormat(np.sum(tmdb_overview_len >= 30)))
print('The number of movie overviews with no less than 50 words: {}'.f
ormat(np.sum(tmdb_overview_len >= 50)))
print('The number of movie overviews with no less than 100 words: {}'.
format(np.sum(tmdb_overview_len >= 100)))
```

```
The number of movie overviews with no less than 20 words: 20007
The number of movie overviews with no less than 50 words: 11830
The number of movie overviews with no less than 100 words: 3282
```



Genre Biclustering

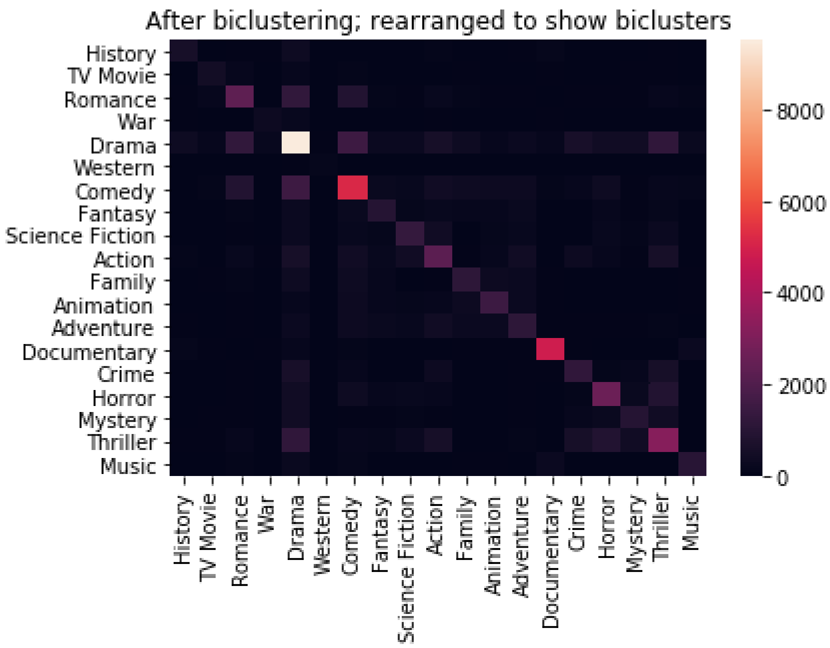
In [9]:
```
Genre_ID_to_name={}
for i in range(len(tmdb_genres_list)):
    genre_id=i
    genre_name=tmdb_genres_list[i]
    Genre_ID_to_name[genre_id]=genre_name
```

In [10]:
```
# This function just generates all possible pairs of movies
def list2pairs(l):
    # itertools.combinations(l,2) makes all pairs of length 2 from lis
t l.
    pairs = list(itertools.combinations(l, 2))
    # then the one item pairs, as duplicate pairs aren't accounted for
 by itertools
    for i in l:
        pairs.append([i,i])
    return pairs
```

In [11]:
```
allPairs = []
for movie in movies:
    allPairs.extend(list2pairs(movie['genre_ids']))
```

In [12]:
```
nr_ids = np.unique(allPairs)
visGrid = np.zeros((len(nr_ids), len(nr_ids)))
for p in allPairs:
    visGrid[np.argwhere(nr_ids==p[0]), np.argwhere(nr_ids==p[1])]+=1
    if p[1] != p[0]:
        visGrid[np.argwhere(nr_ids==p[1]), np.argwhere(nr_ids==p[0])]+
=1
```

In [13]:
```
from sklearn.cluster import SpectralCoclustering
model = SpectralCoclustering(n_clusters=6)
model.fit(visGrid)

fit_data = visGrid[np.argsort(model.row_labels_)]
fit_data = fit_data[:, np.argsort(model.column_labels_)]

annot_lookup_sorted = []
for i in np.argsort(model.row_labels_):
    annot_lookup_sorted.append(Genre_ID_to_name[nr_ids[i]])

sns.heatmap(fit_data, xticklabels=annot_lookup_sorted, yticklabels=ann
ot_lookup_sorted, annot=False)
plt.title("After biclustering; rearranged to show biclusters")

plt.show()
```

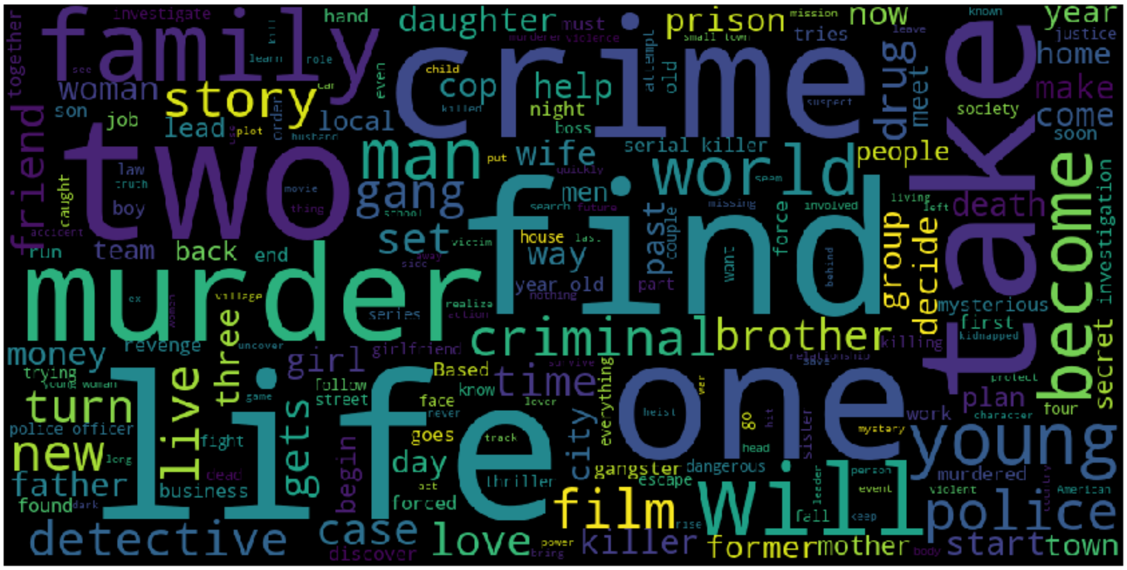


Word Cloud

In [14]:
```
description_crime = np.array([m['overview'] for m in tmdb_all if 4 in
m['genre_ids']])
```

In [15]:
```python
from wordcloud import WordCloud
wordcloud = WordCloud(width = 1000, height = 500).generate(''.join(des
cription_crime));
plt.figure(figsize=(15,8));
plt.imshow(wordcloud);
plt.title('word cloud of crime movie')
plt.axis('off');
```

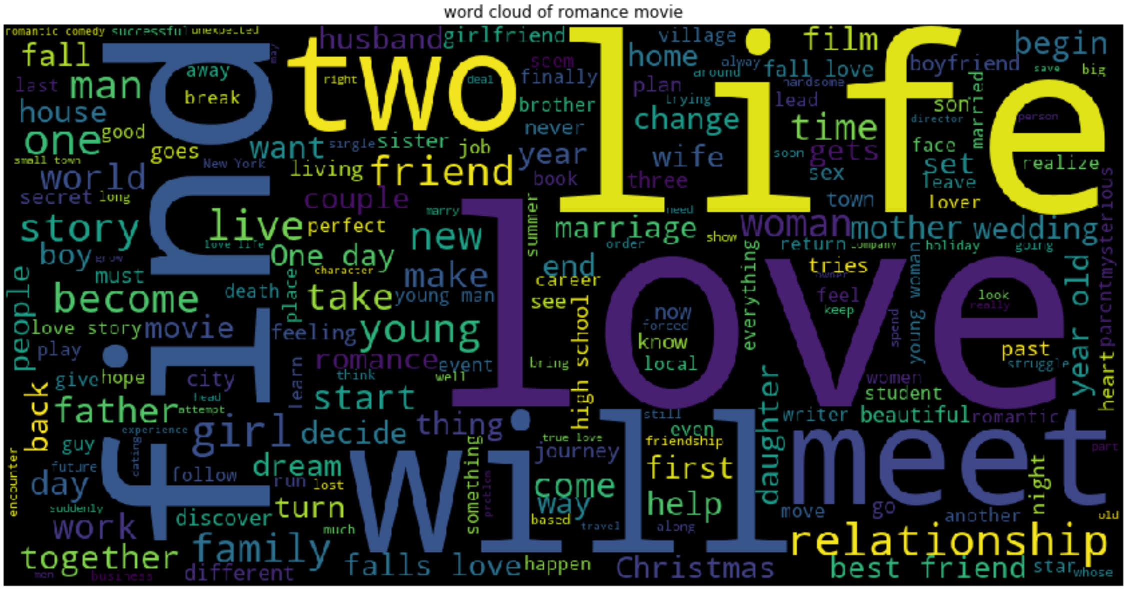
word cloud of crime movie



In [16]:
```python
description_romance = np.array([m['overview'] for m in tmdb_all if 13
in m['genre_ids']])
```

In [17]:
```python
wordcloud = WordCloud(width = 1000, height = 500).generate(''.join(des
cription_romance));
plt.figure(figsize=(15,8));
plt.imshow(wordcloud);
plt.title('word cloud of romance movie')
plt.axis('off');
```

word cloud of romance movie



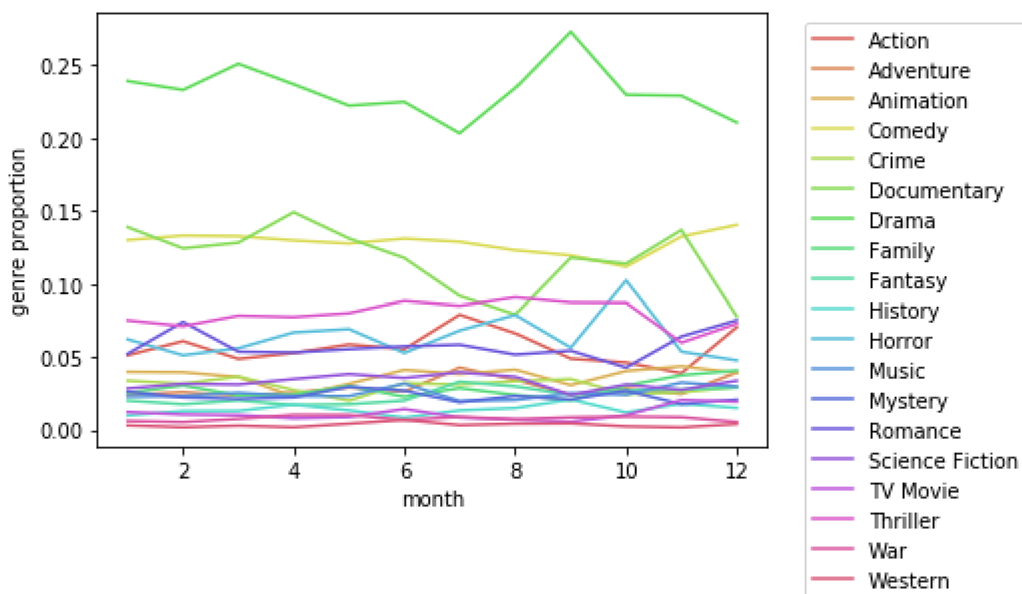
Other features

In [18]:
```
month = np.zeros([12, 19])

for i in range(19):
    for m in movies:
        if i in m['genre_ids']:
            month[int(m['release_date'].split('-')[1]) - 1, i] +=1
```

In [19]:
```
for t in range(12):
    month[t,:] /= month[t,:].sum()
```

In [20]:
```
sns.set_palette("hls", 12)
for i in range(19):
    plt.plot(range(1,13), month[:,i], label = Genre_ID_to_name[i], col
or = color[i])

plt.xlabel('month')
plt.ylabel('genre proportion')
plt.legend(bbox_to_anchor=(1.04,1))
```

Out[20]: <matplotlib.legend.Legend at 0x7f6de685a4e0>



SVM and NaiveBayes (Bag of Words)

In [21]:

```
from sklearn.naive_bayes import MultinomialNB
from sklearn.multiclass import OneVsRestClassifier
from sklearn.svm import LinearSVC

X_train = train.get_data(OVERVIEWS)
X_val = val.get_data(OVERVIEWS)
X_test = test.get_data(OVERVIEWS)
Y_train = train.get_data(GENRES)
Y_val = val.get_data(GENRES)
Y_test = test.get_data(GENRES)

X_train = [" ".join([str(e) for e in x]) for x in X_train]
X_val = [" ".join([str(e) for e in x]) for x in X_val]
X_test = [" ".join([str(e) for e in x]) for x in X_test]

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
cv = CountVectorizer()

X_train_cv = cv.fit_transform(X_train)
X_val_cv = cv.transform(X_val)
X_test_cv = cv.transform(X_test)
```

In [22]:

```
svm = OneVsRestClassifier(LinearSVC())
svm.fit(X_train_cv, Y_train)
val_predict_svm = svm.predict(X_val_cv)
test_predict_svm = svm.predict(X_test_cv)
report(Y_val, val_predict_svm)
report(Y_test, test_predict_svm)
```

```
acc: 0.932438596491228  f1: 0.5013595752945745
acc: 0.9323508771929824         f1: 0.49223070845404265
```

In [23]:

```
cv = CountVectorizer(max_df=0.95, min_df=0.005)

X_train_cv = cv.fit_transform(X_train)
X_val_cv = cv.transform(X_val)
X_test_cv = cv.transform(X_test)

nb = OneVsRestClassifier(MultinomialNB())
nb.fit(X_train_cv, Y_train)
val_predict_nb = nb.predict(X_val_cv)
test_predict_nb = nb.predict(X_test_cv)
report(Y_val, val_predict_nb)
report(Y_test, test_predict_nb)
```

```
acc: 0.9071228070175439         f1: 0.4241896889275614
acc: 0.9065438596491229         f1: 0.42417035996108526
```

The performance of SVM is better than NB in our experiment.

tf-idf

In [24]:
```
tfidf = TfidfTransformer()
X_train_tfidf = tfidf.fit_transform(X_train_cv)
X_val_tfidf = tfidf.transform(X_val_cv)
X_test_tfidf = tfidf.transform(X_test_cv)
```

In [25]:
```
svm = OneVsRestClassifier(LinearSVC())
svm.fit(X_train_tfidf, Y_train)
val_predict_svm = svm.predict(X_val_tfidf)
test_predict_svm = svm.predict(X_test_tfidf)
report(Y_val, val_predict_svm)
report(Y_test, test_predict_svm)
```

```
acc: 0.9347719298245615         f1: 0.3320158102766798
acc: 0.9348947368421053         f1: 0.3219440891649918
```

In [26]:
```
cv = CountVectorizer(max_df=0.95, min_df=0.005)

X_train_cv = cv.fit_transform(X_train)
X_val_cv = cv.transform(X_val)
X_test_cv = cv.transform(X_test)
X_train_tfidf = tfidf.fit_transform(X_train_cv)
X_val_tfidf = tfidf.transform(X_val_cv)
X_test_tfidf = tfidf.transform(X_test_cv)

nb = OneVsRestClassifier(MultinomialNB())
nb.fit(X_train_tfidf, Y_train)
val_predict_nb = nb.predict(X_val_tfidf)
test_predict_nb = nb.predict(X_test_tfidf)
report(Y_val, val_predict_nb)
report(Y_test, test_predict_nb)
```

```
acc: 0.9313333333333333         f1: 0.1397802197802198
acc: 0.9323333333333332         f1: 0.14345991561181437
```

tfidf doesn't improve the performance of our model.

word2vec Embeddings

In [27]:
```
from gensim import models
model2 = models.KeyedVectors.load_word2vec_format('../local/GoogleNews
-vectors-negative300.bin', binary=True)
OVERVIEWS_RAW = load_data("../local/overviews.pkl")
```

In [28]:

```
from nltk.tokenize import RegexpTokenizer
from stop_words import get_stop_words
tokenizer = RegexpTokenizer(r'\w+')

# create English stop words list
en_stop = get_stop_words('en')

movie_mean_wordvec=np.zeros((len(OVERVIEWS_RAW),300))

# get mean word2vec embeddings
for i in range(len(OVERVIEWS_RAW)):
    text = OVERVIEWS_RAW.data[i]
    tokens = filter(lambda x:x not in en_stop, map(lambda x:x.lower(),
 tokenizer.tokenize(text)))
    tokens = filter(lambda x:x in model2.vocab, tokens)
    embs = map(lambda x:model2[x], tokens)

    embs = np.array(list(embs))
    embs = np.mean(embs, axis=0)

    movie_mean_wordvec[i,:] = embs
```

In [29]:

```
WORD2VEC = Data(movie_mean_wordvec)

X_train = train.get_data(WORD2VEC)
X_val = val.get_data(WORD2VEC)
X_test = test.get_data(WORD2VEC)
Y_train = train.get_data(GENRES)
Y_val = val.get_data(GENRES)
Y_test = test.get_data(GENRES)
```

In [30]:

```
svm = OneVsRestClassifier(LinearSVC())
svm.fit(X_train, Y_train)
val_predict_w2v = svm.predict(X_val)
test_predict_w2v = svm.predict(X_test)
report(Y_val, val_predict_w2v)
report(Y_test, test_predict_w2v)
```

```
acc: 0.9332280701754385         f1: 0.28323917137476456
acc: 0.9342807017543858         f1: 0.27933820700269335
```

Deep Learning

Text-Only Model

The model is composed of an encoder and a classifier. The encoder definition is:

```
class Encoder2(torch.nn.Module):
    def __init__(self, encoder, embedding, hidden_dim, input_channel, num_la
yers, bidirectional, dropout, cuda):
        super().__init__()
        self.hidden_dim = hidden_dim
        self.embedding = embedding
        self.bidirectional = bidirectional
        self.cuda = cuda

        self.encoder = encoder(input_size=input_channel, hidden_size=hidden_
dim, batch_first=True,
                                bidirectional=bidirectional, num_layers=num_
layers, dropout=dropout)

        if cuda:
            self.embedding.cuda()
            self.encoder.cuda()

    def forward(self, pack:Pack):
        rev = pack.get_rev()
        data = pack.get_pack(self.embedding, torch_var=True)
        if self.cuda:
            rev.cuda()
        states_packed, _ = self.encoder(data) # (packed_sequence, hidden_sta
te)
        states, _ = torch.nn.utils.rnn.pad_packed_sequence(states_packed)
        states = torch.cat([states[-1,:,:self.hidden_dim], states[0,:,self.h
idden_dim:]], dim=1)
        return states[rev, :]

    def init_hidden(self):
        pass
```

The classifier definition is:

```
class BRClassifier(torch.nn.Module):
    def __init__(self, dims, num_class, encoding_size, cuda):
        super().__init__()

        self.classifiers = []
        for i in range(num_class):
            cls = MultiLayerFCReLUClassifier(dims, 1, encoding_size, cuda)
            self.add_module(str(i), cls)
            self.classifiers.append(cls)

    def forward(self, encodings):
        out = torch.stack([cls(encodings) for cls in self.classifiers])[:,:,
0]
        return torch.transpose(out,0,1)
```

where MultiLayerFCReLUClassifier is defined as:

class MultiLayerFCReLUClassifier(torch.nn.Module):

In [31]:
```
import torch

embedding = torch.load('../local/embedding.pth').cuda()

from cls import BRClassifier
from torch_models import Encoder2
from model import TextOnlyModel
from train import train_epoches

classifier = BRClassifier(dims=[1024, 512], num_class=19, encoding_siz
e=1024, cuda=True)
encoder = Encoder2(encoder=torch.nn.LSTM, embedding=embedding, input_c
hannel=embedding.embedding_dim,
                  hidden_dim=512, num_layers=3, cuda=True, bidirection
al=True, dropout=0)

# replace torch.nn.LSTM by torch.nn.GRU to use GRU
# change num_layers, hidden_dim, bidirectional to experiment with diff
erent configs
# dropout isn't very useful, we tried and it led to underfit.

model = TextOnlyModel(encoder, classifier, OVERVIEWS_ENCODED, GENRES)
loss = torch.nn.BCEWithLogitsLoss().cuda()
adam = torch.optim.Adam(filter(lambda p:p.requires_grad, model.paramet
ers()))

optimizer = adam
scheduler = None

loss_hist = []
save_per_epoch = 10
n_epochs = 0 # change this to train

for i in range(int(n_epochs/save_per_epoch)):
    epoch_losses = train_epoches(n_epochs=save_per_epoch, model=model,
 train=train, loss=loss, val=val,
                  batch_size=32, optimizer=optimizer, scheduler=schedu
ler)
    loss_hist.append(epoch_losses)
    bn = (i+1)*save_per_epoch
    torch.save(model.encoder, "/tmp/encoder_{}_{}.pth".format(bn, str(
epoch_losses[1][1][-1])[:4]))
    torch.save(model.classifier, "/tmp/cls_{}_{}.pth".format(bn, str(e
poch_losses[1][1][-1])[:4]))
```

In [32]:
```
from utils import evaluate, inference
encoder = torch.load("./saved/overview-lstm2/encoder_70_0.53.pth")
encoder.encoder.cuda()
classifier = torch.load("./saved/overview-lstm2/cls_70_0.53.pth").cuda
()
model = TextOnlyModel(encoder, classifier, OVERVIEWS_ENCODED, GENRES)
Yp_val, Yt_val = inference(split=val, model=model, batch_size=128)
Yp_test, Yt_test = inference(split=test, model=model, batch_size=128)
```

In [33]:
```
report(Yt_val, Yp_val)
report(Yt_test, Yp_test)
del model, encoder, classifier, optimizer, scheduler, adam, loss
```

```
acc: 0.9354561403508772         f1: 0.5327067191667725
acc: 0.9342456140350878         f1: 0.5147591921284308
```

Our RNN performs better than all previous models. But what about we do something more interesting? Like using the posters?

Poster-Only Model

We need to preprocess the posters. We assume posters are in ../local/posters. We need to copy posters.npy from tmp to ../local after preprocessing. We essentially convert images into matrices, and apply the transformation required by the torchvision models.

In [34]:
```
import cv2
import os

from torchvision import transforms

# For efficiency we load all images into RAM and do the preprocessing.
 This requires A LOT OF RAM space.
# Instead the images could be processes individually and combined afte
rwards.
if False:
    normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                     std=[0.229, 0.224, 0.225])
    toTensor = transforms.ToTensor()
    preprocess = transforms.Compose([toTensor, normalize])

    images_list = []

    image_folder = "../local/posters/"
    for i in range(30000):
        f = os.path.join(image_folder, "{}.jpg".format(i))
        I = cv2.imread(f)
        assert(I is not None)
        I = preprocess(I)
        images_list.append(I.numpy())

    images = np.stack(images_list)

    POSTERS = Data(images)
    assert(len(POSTERS)==30000)
    POSTERS.save("/tmp/posters.npy")
```

The structure of poster-only model is very similar to TextOnlyModel, except for that now the encoder is replaced by CNN. We tried both VGG16 and RESNET152 as our encoder, and found RES152 is better.

In [35]:
```
from torchvision.models import resnet152, vgg16
from model import PosterOnlyModel

POSTERS = load_data("../local/posters.npy")

if True:
    MODEL = resnet152(pretrained=True)
    # Freeze base layers
    for child in list(MODEL.children())[:-3]:
        for param in child.parameters():
            param.requires_grad = False
    MODEL = torch.nn.Sequential(*list(MODEL.children())[:-1]).cuda()

    # Conv4, turn off grad in first 2 blocks
    for child in list(list(MODEL.children())[-3].children())[:2]:
        for param in child.parameters():
            param.requires_grad = False
else:
    # in order to use VGG16, just use the following code instead of th
e code above
    MODEL = vgg16(pretrained=True)
    # Freeze base layers (except for the last three conv layers)
    for child in list(MODEL.features.children())[:-7]:
        for param in child.parameters():
            param.requires_grad = False
    MODEL = MODEL.features.cuda()

classifier = BRClassifier(dims=[1024, 512], num_class=19, encoding_siz
e=2048, cuda=True)

model = PosterOnlyModel(MODEL, classifier, POSTERS, GENRES)

adam = torch.optim.Adam(filter(lambda p:p.requires_grad, model.paramet
ers()))

optimizer = adam
scheduler = None

loss = torch.nn.BCEWithLogitsLoss().cuda()

n_epochs = 0 # change this to train
save_per_epoch = 10
for i in range(int(n_epochs/save_per_epoch)):
    epoch_losses = train_epoches(n_epochs=save_per_epoch, model=model,
 train=train, loss=loss, val=val,
                  batch_size=16, optimizer=optimizer, scheduler=schedu
ler)
    loss_hist.append(epoch_losses)
    bn = (i+1)*save_per_epoch
    torch.save(model.encoder, "/tmp/cnn_encoder_{}_{}.pth".format(bn,
str(epoch_losses[1][1][-1])[:4]))
    torch.save(model.classifier, "/tmp/cnn_cls_{}_{}.pth".format(bn, s
tr(epoch_losses[1][1][-1])[:4]))
```

In [36]:
```
# our model was trained using pytorch 3. Pytorch 4 was released a week
 before the due date
#  and this function is necessary to run saved pytorch 3 CNN model on
 pytorch 4.
def migrate_pt3_pt4(module):
    if  isinstance(module, torch.nn.modules.batchnorm.BatchNorm1d) or
 \
        isinstance(module, torch.nn.modules.batchnorm.BatchNorm2d) or
 \
        isinstance(module, torch.nn.modules.batchnorm.BatchNorm3d):
        module.track_running_stats = True
    for c in module.children():
        migrate_pt3_pt4(c)
```

In [37]:
```
encoder = torch.load("./saved/poster-res2/encoder_80_0.45.pth")
migrate_pt3_pt4(encoder)
encoder.cuda()
classifier = torch.load("./saved/poster-res2/cls_80_0.45.pth").cuda()
model = PosterOnlyModel(encoder, classifier, POSTERS, GENRES)
Yp_val, Yt_val = inference(split=val, model=model, batch_size=32)
Yp_test, Yt_test = inference(split=test, model=model, batch_size=32)
```

In [38]:
```
report(Yt_val, Yp_val)
report(Yt_test, Yp_test)
del model, MODEL, classifier, optimizer, scheduler, adam, loss
```

```
acc: 0.9317894736842104        f1: 0.45208568207440814
acc: 0.9302280701754384        f1: 0.4304740083058857
```

The poster-only model is worse than text-only model and several traditional models. But it's not surprising because inferring genre from poster is harder (even for humans) than from overview text. But what if we combine the poster model with text model?

Combined Model

The model is simple, the CNN and RNN operates independently, and the encodings from both networks are then stacked and fed to a classifier.

We wanted to train the combined model, but the GPU RAM is too small! So instead we fixed RNN and CNN, and only train the classifier.

The combined encoder is simple as

```
class TextPosterCombinedEncoder(torch.nn.Module):
    def __init__(self, text_encoder, poster_encoder):
        super().__init__()
        self.text_encoder = text_encoder
        self.poster_encoder = poster_encoder

    def forward(self, text_pack, posters):
        poster_encodings = self.poster_encoder(posters).view(len(posters),-
1)
        text_encodings = self.text_encoder(text_pack)
        return poster_encodings, text_encodings
```

In [39]:

```
from torch_models import TextPosterCombinedEncoder
from model import TextPosterCombinedModel

text_encoder = torch.load("./saved/overview-lstm2/encoder_70_0.53.pth"
)
posters_encoder = torch.load("./saved/poster-res2/encoder_80_0.45.pth"
)

encoder = TextPosterCombinedEncoder(text_encoder, posters_encoder).cud
a()

for param in encoder.parameters():
    param.requires_grad = False

classifier = BRClassifier(dims=[1024, 512], num_class=19, encoding_siz
e=2048+1024, cuda=True)

optimizer = torch.optim.Adam(filter(lambda p:p.requires_grad, classifi
er.parameters()))
loss = torch.nn.BCEWithLogitsLoss().cuda()

scheduler=None

model = TextPosterCombinedModel(encoder, classifier, OVERVIEWS_ENCODED
, POSTERS, GENRES)

n_epochs = 0 # change this to train
save_per_epoch = 4
for i in range(int(n_epochs/save_per_epoch)):
    epoch_losses = train_epoches(n_epochs=save_per_epoch, model=model,
 train=train, loss=loss, val=val,
                  batch_size=32, optimizer=optimizer, scheduler=schedu
ler)
    bn = (i+1)*save_per_epoch
    torch.save(model.classifier, "/tmp/cbn_cls_{}_{}.pth".format(bn, s
tr(epoch_losses[1][1][-1])[:4]))
```

In [40]:

```
classifier = torch.load("./saved/cbn/cls_4_0.54.pth").cuda()
migrate_pt3_pt4(encoder)
model = TextPosterCombinedModel(encoder, classifier, OVERVIEWS_ENCODED
, POSTERS, GENRES)

Yp_val, Yt_val = inference(split=val, model=model, batch_size=32)
Yp_test, Yt_test = inference(split=test, model=model, batch_size=32)
```

In [41]:

```
# get the output unit values (probas) for interpretation
Yp_test_proba, Yt_test_proba = inference(split=test, model=model, batc
h_size=32, proba=True)
np.save("Y_pred_test.npy", Yp_test_proba)
np.save("Y_true_test.npy", Yt_test_proba)
```

In [42]:
```
report(Yt_val, Yp_val)
report(Yt_test, Yp_test)
del model, encoder, classifier, optimizer, scheduler, loss
```

```
acc: 0.945157894736842  f1: 0.5420451215939057
acc: 0.9437543859649123         f1: 0.5186186186186187
```

The result is slightly better than TextOnlyModel thus having the best performance. The result could be better if we don't fix some layers of the RNN and CNN, but it requires more GPU RAM. Maybe training on a more powerful GPU or multiple GPUs is a possible future direction.

Interpretation

1. The combined model using both plot descriptions and posters provides the best result in both validation and test set, slightly higher than RNN models with only text embedding features.
2. For the conventional machine learning models, using bag-of-word representation for text features have better predictability and it gives a result very close to our best model. The reason might be that TMDB plot discription is generally short, so simply identify certain words could be able to distinguish the genres. While using tfidf or embeddings is likely to deviate from this simple feature.
3. Models with only poster information didn't perform well, but combine it with text features could slightly improve our model's performance.

In [43]:

```
import numpy as np
import torch

Y_pred = np.load("./Y_pred_test.npy")
Y_true = np.load("./Y_true_test.npy")
Y_pred_sigmoid = torch.nn.functional.sigmoid(torch.from_numpy(Y_pred))
.numpy()

genres = np.load("../data/tmdb_genres_list.pkl")

results = {}

from sklearn.metrics import f1_score, precision_score, recall_score, r
oc_auc_score, accuracy_score
import pandas as pd

def number(n):
    return "%.2f%%"%(n*100)

def sprint(*args, sep=" ", end="\n"):
    return sep.join([str(s) for s in args])+end

for i in range(len(genres)):
    pred = Y_pred[:, i]>0
    label = Y_true[:, i]
    pred_sigmoid = Y_pred_sigmoid[:, i]
    result = dict([
        ("F1", number(f1_score(label, pred))),
        ("Precision", number(precision_score(label, pred))),
        ("Recall", number(recall_score(label, pred))),
        ("AUC", number(roc_auc_score(label, pred_sigmoid))),
        ("Accuracy", number(accuracy_score(label, pred))),
    ])
    results[genres[i]] = result

df = pd.DataFrame(results, index=["F1", "Precision", "Recall", "Accura
cy", "AUC"]).T
df
```

Out[43]:

	F1	Precision	Recall	Accuracy	AUC
Action	50.31%	61.54%	42.55%	94.73%	86.99%
Adventure	36.64%	66.67%	25.26%	97.23%	87.94%
Animation	45.61%	71.23%	33.55%	95.87%	89.01%
Comedy	53.68%	61.69%	47.51%	85.73%	83.52%
Crime	33.92%	76.32%	21.80%	96.23%	83.47%
Documentary	56.14%	64.36%	49.79%	87.87%	85.37%
Drama	60.30%	60.21%	60.40%	74.77%	79.85%
Family	36.81%	65.22%	25.64%	96.57%	80.32%
Fantasy	32.73%	81.82%	20.45%	97.53%	85.08%
History	44.78%	100.00%	28.85%	98.77%	86.62%
Horror	59.64%	80.56%	47.35%	94.77%	91.53%
Music	31.65%	73.33%	20.18%	96.83%	78.04%
Mystery	40.00%	95.45%	25.30%	97.90%	81.92%
Romance	47.09%	68.99%	35.74%	93.33%	82.59%
Science Fiction	40.00%	83.33%	26.32%	96.50%	86.88%
TV Movie	31.82%	70.00%	20.59%	99.00%	75.12%
Thriller	46.09%	64.84%	35.76%	90.80%	86.01%
War	45.45%	100.00%	29.41%	99.20%	88.00%
Western	40.00%	100.00%	25.00%	99.50%	88.31%

1. All the genre have reasonable F1-score and AUC. Genre with larger sample sizes have better evaluation metrics. The classificaiton model is influenced by unbalanced data set to some degree.
2. TV Movie and Music have the worst AUC and F1 score among all genres. Both of them have limited sample size and are not closely correlated with other genres. There might not be enough training data for our model to specify their unique features.
3. There might be human error in the exisitng ground truth since it is relatively difficult to label certain correlated topics, such as horror and thriller. Therefore, considering these human error, our AUCs are within reasonable range for all genres.