Convex Optimization, HW 10, Chao Ni

In [1]:
```
import numpy as np
import pandas as pd
import cvxpy as cp
import matplotlib.pyplot as plt, imread
import imread
```

In [2]:
```
pokemon = pd.read_csv('pokemon.csv')
pokemon_move = pd.read_csv('pokemon_moves.csv')
type_list = ['normal','fire','fighting','water','flying','grass','poison',
             'electric','ground','psychic','rock','ice','bug','dragon',
             'ghost','dark','steel','fairy']
```

(a) Converting to the matrix B

In [3]:
```
B = np.zeros((len(pokemon),len(type_list)))
for i in range(len(pokemon)):
    if pokemon.loc[i,'type1'] in type_list:
        B[i,type_list.index(pokemon.loc[i,'type1'])]=1
    if pokemon.loc[i,'type2'] in type_list:
        B[i,type_list.index(pokemon.loc[i,'type2'])]=1
```

(b) Creating a matrix M

In [4]:
```
n_move = 728;
M = np.zeros((n_move,len(pokemon)))
for i in range(len(pokemon_move)):
    if (pokemon_move.loc[i,'pokemon_id']>=802):
        break
    M[int(pokemon_move.loc[i,'move_id']-1), int(pokemon_move.loc[i,'pokemon_id']-1)] = 1
```

Test the matrix B and M are corrent

In [5]:
```
M_std = pd.read_csv('ex10_pokemon_moves.csv',header=None)
B_std = pd.read_csv('ex10_pokemon_types.csv',header=None)
print('B difference in Frobenius norm:',np.linalg.norm(B_std.values - B))
print('M difference in Frobenius norm:',np.linalg.norm(M_std.values - M))
```

```
B difference in Frobenius norm: 0.0
M difference in Frobenius norm: 0.0
```

(c,d) Implementing the logistic regression and return the TP, TN, FP, FN

Snorlax test

We train the model with first type normal, (let i=0), and yes the classifier return the Snorlax, which is indexed 142, a normal-type

In [6]:
```
def perf_measure(y_actual, y_hat):
    TP = 0
    FP = 0
    TN = 0
    FN = 0
    for i in range(len(y_hat)):
        if (y_actual[i]==y_hat[i]==1):
            TP += 1
        if y_hat[i]==1 and y_actual[i]!=y_hat[i]:
            FP += 1
        if y_actual[i]==y_hat[i]==0:
            TN += 1
        if y_hat[i]==0 and y_actual[i]!=y_hat[i]:
            FN += 1
    return(TP, FP, TN, FN)
```

In [7]:
```
n_train = 400
df = pd.DataFrame()
for i in range(18):
    name = type_list[i]

    beta = cp.Variable(n_move)
    mid = M[:,0:n_train].T @ beta
    log_likelihood = cp.sum(cp.multiply(B[0:n_train,i], mid) - cp.logistic(mid))
    problem = cp.Problem(cp.Maximize(log_likelihood))
    problem.solve(solver='ECOS',verbose=False)
#     print('solve status',problem.status)
    if problem.status not in ["infeasible", "unbounded","infeasible_inaccurate","unbounded_inaccurate"]:
        TP,FP,TN,FN = perf_measure(B[n_train:801,i],(1+np.sign((M[:,n_train:801].T@beta).value))/2)
        acc = (TP+TN)/(TP+TN+FP+FN)
        new_row = {'name':name,'TP':TP,'TN':TN,'FP':FP,'FN':FN,'ACC':acc}
        df = df.append(new_row,ignore_index=True,sort=False)
```

...

In [12]:
```
# 142 for Snorlax, only use when beta is trained with label "normal", i.e. i=0
print((1+np.sign((M[:,142].T@beta).value))/2)
```

```
1.0
```

with training number 400

In [10]:
```
df
```

Out[10]:

	ACC	FN	FP	TN	TP	name
0	0.875312	16.0	34.0	318.0	33.0	normal
1	0.932668	10.0	17.0	352.0	22.0	fire
2	0.912718	25.0	10.0	358.0	8.0	fighting
3	0.927681	7.0	22.0	330.0	42.0	water
4	0.917706	16.0	17.0	339.0	29.0	flying
5	0.892768	33.0	10.0	338.0	20.0	grass
6	0.832918	12.0	55.0	324.0	10.0	poison
7	0.947631	7.0	14.0	361.0	19.0	electric
8	0.897756	20.0	21.0	354.0	6.0	ground
9	0.815461	4.0	70.0	293.0	34.0	psychic
10	0.897756	15.0	26.0	346.0	14.0	rock
11	0.957606	9.0	8.0	375.0	9.0	ice
12	0.940150	21.0	3.0	357.0	20.0	bug
13	0.972569	4.0	7.0	363.0	27.0	dragon
14	0.920200	22.0	10.0	360.0	9.0	ghost
15	0.922693	16.0	15.0	356.0	14.0	dark
16	0.942643	11.0	12.0	359.0	19.0	steel
17	0.915212	27.0	7.0	365.0	2.0	fairy

(e) Which is most accurate?

Based on the accuracy measurement I defined, dragon is the type for which the classifier is the most accurate, and poison is the least accurate.

Unfortunately I don't have lots of knowledge about Pokeman. Based on my limited experience, I think dragon type is rare and poison is quite common in Pokeman, which means lots of different pokeman have this function.

(f) Plot for different training data

Besides three ratios indicated in the homework, I also include another ratio defined as $r_4 = \frac{TP+TN}{TP+TN+FP+FN}$

From the pictures and the tables we ploted already, we found that most of samples are ture negative. And the rest three categories are relatively random. For r_1, if it is smaller, it means the false positive are relatively smaller, which means a higher precision. For r_2, it it is smaller, it also means the classifier is relatively more accurate in term of higher precision in recognizing negativeness. But because true negative is big and r_2 is thus always small, and the difference between training numbers are relatively trivial. And r_3 in some sense combines the previous two measurements, which I think is the best of three. And I also propose another performance measurement r_4.

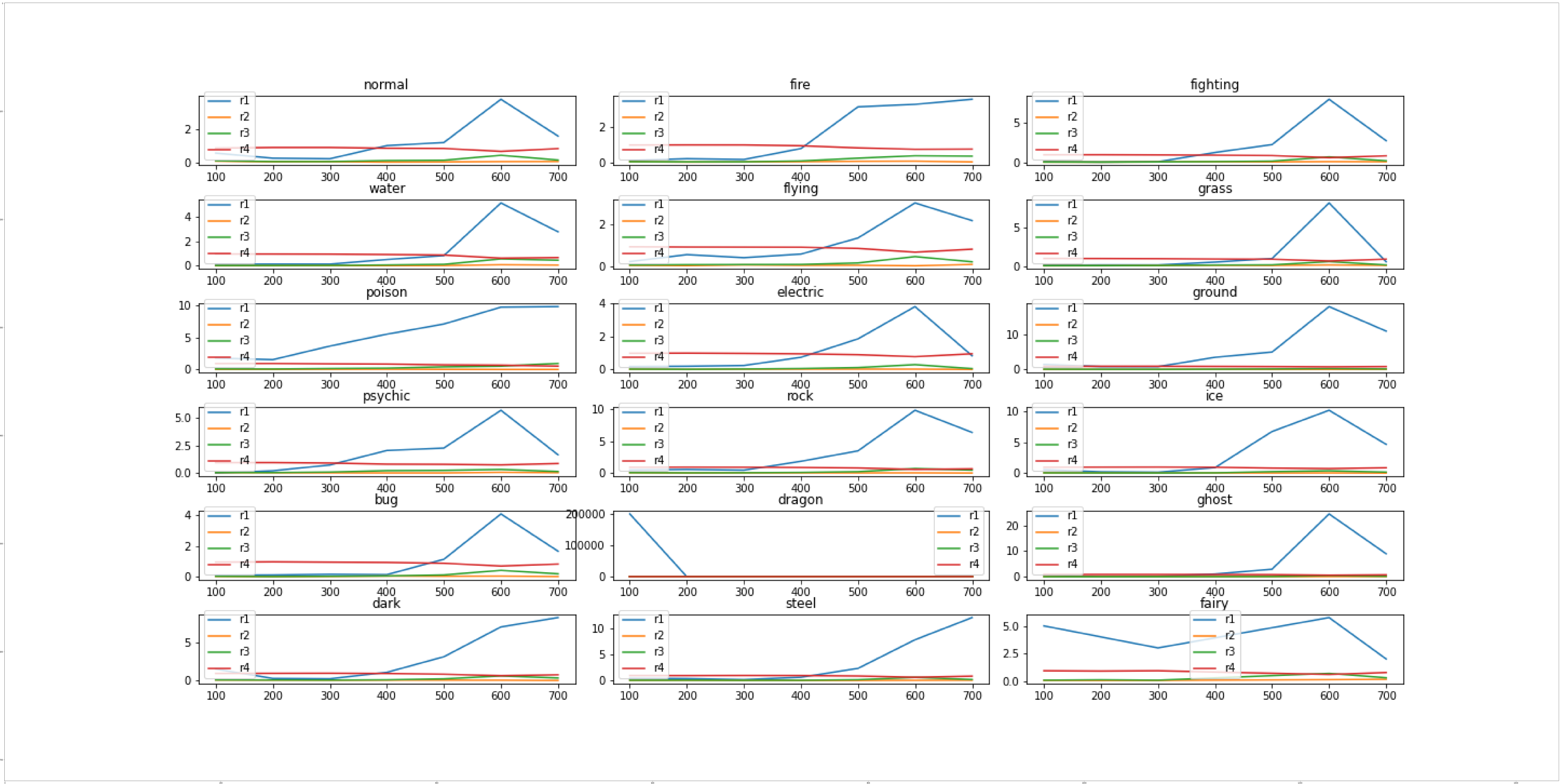
In [20]:
```
n_train_list = [100,200,300,400,500,600,700]
fig = plt.figure(figsize=(20,10))
fig.subplots_adjust(wspace=0.1,
                    hspace=0.5)
fig.tight_layout()
for i in range(18):
    name = type_list[i]
    r1 = []
    r2 = []
    r3 = []
    r4 = []
    plot_list = []
    for n_train in n_train_list:

        beta = cp.Variable(n_move)
        mid = M[:,0:n_train].T @ beta
        log_likelihood = cp.sum(cp.multiply(B[0:n_train,i], mid) - cp.logistic(mid))
        problem = cp.Problem(cp.Maximize(log_likelihood))
        if (i==17):
            solver = 'SCS'
        else:
            solver = 'ECOS'
        problem.solve(solver=solver,verbose=False)
        print('solve status',problem.status)
        if problem.status not in ["infeasible", "unbounded","infeasible_inaccurate","unbounded_inaccurate"]:
            TP,FP,TN,FN = perf_measure(B[n_train:801,i],(1+np.sign((M[:,n_train:801].T@beta).value))/2)
            r1.append(FP/(TP+1e-5))
            r2.append(FN/(TN+1e-5))
            r3.append((FP+FN)/(TP+TN+1e-5))
            r4.append((TP+TN)/(TP+TN+FP+FN+1e-5))
            plot_list.append(n_train)
    plt.subplot(6,3,i+1)
    plt.plot(plot_list,r1);
    plt.plot(plot_list,r2);
    plt.plot(plot_list,r3);
    plt.plot(plot_list,r4);
    plt.legend(labels=['r1','r2','r3','r4'],loc='best')
    plt.title(name)

plt.savefig('fool.png')
```

. . .

In [2]:
```
image = plt.imread('fool.png')
plt.figure(figsize=(150,150))
plt.imshow(image)
plt.show()
```



(g) Dual-type

I would choose the optimal training number as 500. If we choose too less samples for training, then the problem might be underfitting, while if we select too many samples, the problem would be overfitting and thus lose generalization. I would say out of 800 samples, 500 for training is a reasonable number. And also from the graph, in term of r_3 and r_4, we know at 500 they reaches a low level and then increase again at 600.

Therefore, I would say 500. After separating training and test data and splitting the test data into single and dual types. I have the following solution. In terms of r_3, which as discussed above is the best of three measurements or in term of r_4, for single-type pokemon, the classifier is more accurate; for dual-type pokemon, however, the classifier is less accurate.

In [7]:
```
def get_single_dual_type_test(B,n_train):
    single_list = []
    dual_list = []
    n,m = B.shape
    for i in range(n_train, 801):
        if (np.sum(B[i,:])==1):
            single_list.append(i)
        elif (np.sum(B[i,:])==2):
            dual_list.append(i)
    return single_list, dual_list
```

In [9]:
```
# choose the best
n_train = 500
single_list, dual_list = get_single_dual_type_test(B,n_train)
df_s = pd.DataFrame()
df_d = pd.DataFrame()
df = pd.DataFrame()
for i in range(18):
    name = type_list[i]

    beta = cp.Variable(n_move)
    mid = M[:,0:n_train].T @ beta
    log_likelihood = cp.sum(cp.multiply(B[0:n_train,i], mid) - cp.logistic(mid))
    problem = cp.Problem(cp.Maximize(log_likelihood))
    solver = 'ECOS'
    problem.solve(solver=solver,verbose=False)
    print('solve status',problem.status)
    if problem.status not in ["infeasible", "unbounded","infeasible_inaccurate","unbounded_inaccurate"]:

        # single type
        TP,FP,TN,FN = perf_measure(B[single_list,i],(1+np.sign((M[:,single_list].T@beta).value))/2)
        new_row = {'name':name,'TP':TP,'TN':TN,'FP':FP,'FN':FN,'r1':FP/(TP+1e-5),'r2':FN/(TN+1e-5),
                   'r3':(FP+FN)/(TP+TN+1e-5),'r4':(TP+TN)/(TP+TN+FP+FN+1e-5)}
        df_s = df_s.append(new_row,ignore_index=True,sort=False)

        # dual type
        TP,FP,TN,FN = perf_measure(B[dual_list,i],(1+np.sign((M[:,dual_list].T@beta).value))/2)
        new_row = {'name':name,'TP':TP,'TN':TN,'FP':FP,'FN':FN,'r1':FP/(TP+1e-5),'r2':FN/(TN+1e-5),
                   'r3':(FP+FN)/(TP+TN+1e-5),'r4':(TP+TN)/(TP+TN+FP+FN+1e-5)}
        df_d = df_d.append(new_row,ignore_index=True,sort=False)

        # all_type
        TP,FP,TN,FN = perf_measure(B[n_train:801,i],(1+np.sign((M[:,n_train:801].T@beta).value))/2)
        new_row = {'name':name,'TP':TP,'TN':TN,'FP':FP,'FN':FN,'r1':FP/(TP+1e-5),'r2':FN/(TN+1e-5),
                   'r3':(FP+FN)/(TP+TN+1e-5),'r4':(TP+TN)/(TP+TN+FP+FN+1e-5)}
        df = df.append(new_row,ignore_index=True,sort=False)
```

...

single-type pokeman

In [10]:
```
df_s
```

Out[10]:

	FN	FP	TN	TP	name	r1	r2	r3	r4
0	5.0	12.0	110.0	11.0	normal	1.090908	0.045455	0.140496	0.876812
1	4.0	26.0	103.0	5.0	fire	5.199990	0.038835	0.277778	0.782609
2	4.0	14.0	114.0	6.0	fighting	2.333329	0.035088	0.150000	0.869565
3	1.0	16.0	106.0	15.0	water	1.066666	0.009434	0.140496	0.876812
4	0.0	11.0	126.0	1.0	flying	10.999890	0.000000	0.086614	0.920290
5	2.0	14.0	110.0	12.0	grass	1.166666	0.018182	0.131148	0.884058
6	0.0	42.0	94.0	2.0	poison	20.999895	0.000000	0.437500	0.695652
7	2.0	16.0	116.0	4.0	electric	3.999990	0.017241	0.150000	0.869565
8	1.0	18.0	117.0	2.0	ground	8.999955	0.008547	0.159664	0.862319
9	1.0	20.0	103.0	14.0	psychic	1.428570	0.009709	0.179487	0.847826
10	1.0	24.0	109.0	4.0	rock	5.999985	0.009174	0.221239	0.818841
11	3.0	27.0	103.0	5.0	ice	5.399989	0.029126	0.277778	0.782609
12	1.0	13.0	119.0	5.0	bug	2.599995	0.008403	0.112903	0.898551
13	0.0	11.0	119.0	8.0	dragon	1.374998	0.000000	0.086614	0.920290
14	0.0	9.0	127.0	2.0	ghost	4.499978	0.000000	0.069767	0.934783
15	0.0	22.0	112.0	4.0	dark	5.499986	0.000000	0.189655	0.840580
16	0.0	19.0	116.0	3.0	steel	6.333312	0.000000	0.159664	0.862319
17	5.0	30.0	98.0	5.0	fairy	5.999988	0.051020	0.339806	0.746377

dual-type pokemon

In [11]:
```
df_d
```

Out[11]:

	FN	FP	TN	TP	name	r1	r2	r3	r4
0	9.0	16.0	126.0	12.0	normal	1.333332	0.071429	0.181159	0.846626
1	8.0	18.0	128.0	9.0	fire	1.999998	0.062500	0.189781	0.840491
2	10.0	13.0	134.0	6.0	fighting	2.166663	0.074627	0.164286	0.858896
3	6.0	11.0	129.0	17.0	water	0.647058	0.046512	0.116438	0.895705
4	12.0	19.0	111.0	21.0	flying	0.904761	0.108108	0.234848	0.809816
5	15.0	7.0	131.0	10.0	grass	0.699999	0.114504	0.156028	0.865031
6	2.0	43.0	108.0	10.0	poison	4.299996	0.018519	0.381356	0.723926
7	3.0	10.0	140.0	10.0	electric	0.999999	0.021429	0.086667	0.920245
8	9.0	17.0	132.0	5.0	ground	3.399993	0.068182	0.189781	0.840491
9	2.0	37.0	113.0	11.0	psychic	3.363633	0.017699	0.314516	0.760736
10	7.0	25.0	121.0	10.0	rock	2.499998	0.057851	0.244275	0.803681
11	1.0	27.0	132.0	3.0	ice	8.999970	0.007576	0.207407	0.828221
12	10.0	11.0	126.0	16.0	bug	0.687500	0.079365	0.147887	0.871166
13	0.0	7.0	139.0	17.0	dragon	0.411764	0.000000	0.044872	0.957055
14	17.0	9.0	133.0	4.0	ghost	2.249994	0.127820	0.189781	0.840491
15	9.0	22.0	122.0	10.0	dark	2.199998	0.073770	0.234848	0.809816
16	5.0	18.0	127.0	13.0	steel	1.384614	0.039370	0.164286	0.858896
17	13.0	17.0	129.0	4.0	fairy	4.249989	0.100775	0.225564	0.815951

for all pokemon

In [12]:
```
df
```

Out[12]:

	FN	FP	TN	TP	name	r1	r2	r3	r4
0	14.0	28.0	236.0	23.0	normal	1.217391	0.059322	0.162162	0.860465
1	12.0	44.0	231.0	14.0	fire	3.142855	0.051948	0.228571	0.813953
2	14.0	27.0	248.0	12.0	fighting	2.249998	0.056452	0.157692	0.863787
3	7.0	27.0	235.0	32.0	water	0.843750	0.029787	0.127341	0.887043
4	12.0	30.0	237.0	22.0	flying	1.363636	0.050633	0.162162	0.860465
5	17.0	21.0	241.0	22.0	grass	0.954545	0.070539	0.144487	0.873754
6	2.0	85.0	202.0	12.0	poison	7.083327	0.009901	0.406542	0.710963
7	5.0	26.0	256.0	14.0	electric	1.857142	0.019531	0.114815	0.897010
8	10.0	35.0	249.0	7.0	ground	4.999993	0.040161	0.175781	0.850498
9	3.0	57.0	216.0	25.0	psychic	2.279999	0.013889	0.248963	0.800664
10	8.0	49.0	230.0	14.0	rock	3.499998	0.034783	0.233607	0.810631
11	4.0	54.0	235.0	8.0	ice	6.749992	0.017021	0.238683	0.807309
12	11.0	24.0	245.0	21.0	bug	1.142857	0.044898	0.131579	0.883721
13	0.0	18.0	258.0	25.0	dragon	0.720000	0.000000	0.063604	0.940199
14	17.0	18.0	260.0	6.0	ghost	2.999995	0.065385	0.131579	0.883721
15	9.0	44.0	234.0	14.0	dark	3.142855	0.038462	0.213710	0.823920
16	5.0	37.0	243.0	16.0	steel	2.312499	0.020576	0.162162	0.860465
17	18.0	47.0	227.0	9.0	fairy	5.222216	0.079295	0.275424	0.784053

In [16]:
```
[df_s['r1'].mean(),df_s['r2'].mean(),df_s['r3'].mean(),df_s['r4'].mean()]
```

Out[16]:
```
[5.277449469859531,
 0.015567466174363331,
 0.18392268873645007,
 0.8494363313612963]
```

In [17]:
```
[df_d['r1'].mean(),df_d['r2'].mean(),df_d['r3'].mean(),df_d['r4'].mean()]
```

Out[17]:
```
[2.3610700489919934,
 0.06055746202777764,
 0.19298785120944298,
 0.8415132408069587]
```

In [18]:
```
[df['r1'].mean(),df['r2'].mean(),df['r3'].mean(),df['r4'].mean()]
```

Out[18]:
```
[2.8768358583720914,
 0.03903234942095439,
 0.18771464470643895,
 0.8451457821841564]
```