In [ ]:
```
import pandas as pd
# for precision and recall measurements
from sklearn import metrics as mt


# toy example data

row_number = [1, 2, 3, 4, 5, 6, 7, 8, 9]

names = ['Ali', 'Emilio', 'Tom', 'Julie', 'Ignacio', 'Ugo', 'Yuqi', 'Meagan', 'Andrea']

reported_gender = ['male', 'male', 'male', 'female', 'male', 'male', 'female', 'female', 'male']

predicted_gender = ['female', 'male', 'male', 'female', 'female', 'male', 'male', 'female', 'female

df = pd.DataFrame({'row_number': row_number,
                   'names':names,
                    'reported_gender': reported_gender,
                    'predicted_gender': predicted_gender})

df
```

Out[ ]:

	row_number	names	reported_gender	predicted_gender
0	1	Ali	male	female
1	2	Emilio	male	male
2	3	Tom	male	male
3	4	Julie	female	female
4	5	Ignacio	male	female
5	6	Ugo	male	male
6	7	Yuqi	female	male
7	8	Meagan	female	female
8	9	Andrea	male	female

In [ ]:
```
TP_m = 1 + 1 + 1

# false positives for males, those reported female who are predicted male
# Yuqi
FP_m = 1

# false negatives for males, those reported male who are predicted female.
# Ali, Ignacio, Andrea
FN_m = 1 + 1 + 1

# true negatives for males, those reported female who are predicted female.
# Julie, Meagan
TN_m = 1 + 1

### now calculation for females
# true positives for females, those reported female who are also predicted female.
# Julie, Meagan
TP_f = 1 + 1

# false positives for females, those reported male who are predicted female
# Ali, Ignacio, Andrea
FP_f = 1 + 1 + 1

# false negatives for females, those reported female who are predicted male.
# Yuqi
FN_f = 1

# true negatives for females, those reported male who are predicted male.
```

```
# Emilio, Tom, Ugo
TN_f = 1 + 1 + 1
```

In [ ]:
```
precision_male = TP_m / (TP_m + FP_m)
print(precision_male)
```

```
0.75
```

In [ ]:
```
recall_male = TP_m / (TP_m + FN_m)
print(recall_male)
```

```
0.5
```

In [ ]:
```
f1_male = 2 * TP_m / (2 * TP_m + FP_m + FN_m)
print(f1_male)
```

```
0.6
```

In [ ]:
```
precision_female = TP_f / (TP_f + FP_f)
print(precision_female)
```

```
0.4
```

In [ ]:
```
recall_female = TP_f / (TP_f + FN_f)
print(recall_female)
```

```
0.6666666666666666
```

In [ ]:
```
f1_female = 2 * TP_f / (2 * TP_f + FP_f + FN_f)
print(f1_female)
```

```
0.5
```

In [ ]:
```
overall_prere = pd.DataFrame(mt.classification_report(df.reported_gender, df.predicted_gender, outp

# add country name
overall_prere['countrycode'] = 'all_countries'

print(overall_prere)
```

```
             female  male  accuracy  macro avg  weighted avg    countrycode
precision  0.400000  0.75  0.555556   0.575000      0.633333  all_countries
recall     0.666667  0.50  0.555556   0.583333      0.555556  all_countries
f1-score   0.500000  0.60  0.555556   0.550000      0.566667  all_countries
support    3.000000  6.00  0.555556   9.000000      9.000000  all_countries
```

In [ ]:
```
reported_country = ['Iran', 'Italy', 'Germany', 'Korea', 'Chile', 'Italy', 'China', 'USA', 'Italy']

affiliation_country = ['Germany', 'Germany', 'Germany', 'USA', 'UK', 'Germany', 'UK', 'USA', 'USA']

df_w_country = pd.DataFrame({'row_number': row_number,
                   'names':names,
                    'reported_gender': reported_gender,
                    'predicted_gender': predicted_gender,
                    'reported_country': reported_country,
                    'affiliation_country': affiliation_country})

df_w_country
```

Out[ ]:

	row_number	names	reported_gender	predicted_gender	reported_country	affiliation_country
0	1	Ali	male	female	Iran	Germany
1	2	Emilio	male	male	Italy	Germany
2	3	Tom	male	male	Germany	Germany
3	4	Julie	female	female	Korea	USA
4	5	Ignacio	male	female	Chile	UK
5	6	Ugo	male	male	Italy	Germany
6	7	Yuqi	female	male	China	UK
7	8	Meagan	female	female	USA	USA
8	9	Andrea	male	female	Italy	USA

In [ ]:

```
results_list = []

# grouped version of data
grouped_df = df_w_country.groupby('affiliation_country')

# with for loop of all countries, it took 77 minutes
for countrycode, country_dt in grouped_df:
    print(countrycode, '\n')
    res = pd.DataFrame(mt.classification_report(country_dt.reported_gender, country_dt.predicted_ge
    res['countrycode'] = countrycode
    results_list.append(res)

results_all = pd.concat(results_list)

# add overall countries
results_all = pd.concat([results_all, overall_prere])

# drop index and rename it
results_all = results_all.reset_index().rename(columns={'index':'metric'})

print(results_all)
```

```
Germany

UK

USA

       metric    female      male  accuracy  macro avg  weighted avg  \
0   precision  0.000000  1.000000  0.750000   0.500000      1.000000
1      recall  0.000000  0.750000  0.750000   0.375000      0.750000
2    f1-score  0.000000  0.857143  0.750000   0.428571      0.857143
3     support  0.000000  4.000000  0.750000   4.000000      4.000000
4   precision  0.000000  0.000000  0.000000   0.000000      0.000000
5      recall  0.000000  0.000000  0.000000   0.000000      0.000000
6    f1-score  0.000000  0.000000  0.000000   0.000000      0.000000
7     support  1.000000  1.000000  0.000000   2.000000      2.000000
8   precision  0.666667  0.000000  0.666667   0.333333      0.444444
9      recall  1.000000  0.000000  0.666667   0.500000      0.666667
10   f1-score  0.800000  0.000000  0.666667   0.400000      0.533333
11    support  2.000000  1.000000  0.666667   3.000000      3.000000
12  precision  0.400000  0.750000  0.555556   0.575000      0.633333
13     recall  0.666667  0.500000  0.555556   0.583333      0.555556
14   f1-score  0.500000  0.600000  0.555556   0.550000      0.566667
15    support  3.000000  6.000000  0.555556   9.000000      9.000000

      countrycode
0         Germany
1         Germany
2         Germany
3         Germany
4              UK
5              UK
6              UK
7              UK
8             USA
9             USA
10            USA
11            USA
12  all_countries
13  all_countries
14  all_countries
15  all_countries
```

```
c:\Users\akbaritabar\AppData\Local\anaconda3\envs\Ali\Lib\site-packages\sklearn\metrics\_classifica
tion.py:1531: UndefinedMetricWarning: Recall is ill-defined and being set to 0.0 in labels with no
true samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
c:\Users\akbaritabar\AppData\Local\anaconda3\envs\Ali\Lib\site-packages\sklearn\metrics\_classifica
tion.py:1531: UndefinedMetricWarning: Recall is ill-defined and being set to 0.0 in labels with no
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true samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
c:\Users\akbaritabar\AppData\Local\anaconda3\envs\Ali\Lib\site-packages\sklearn\metrics\_classifica
tion.py:1531: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with
no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
c:\Users\akbaritabar\AppData\Local\anaconda3\envs\Ali\Lib\site-packages\sklearn\metrics\_classifica
tion.py:1531: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with
no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
c:\Users\akbaritabar\AppData\Local\anaconda3\envs\Ali\Lib\site-packages\sklearn\metrics\_classifica
tion.py:1531: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with
no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

In [ ]:

```
results_all
```

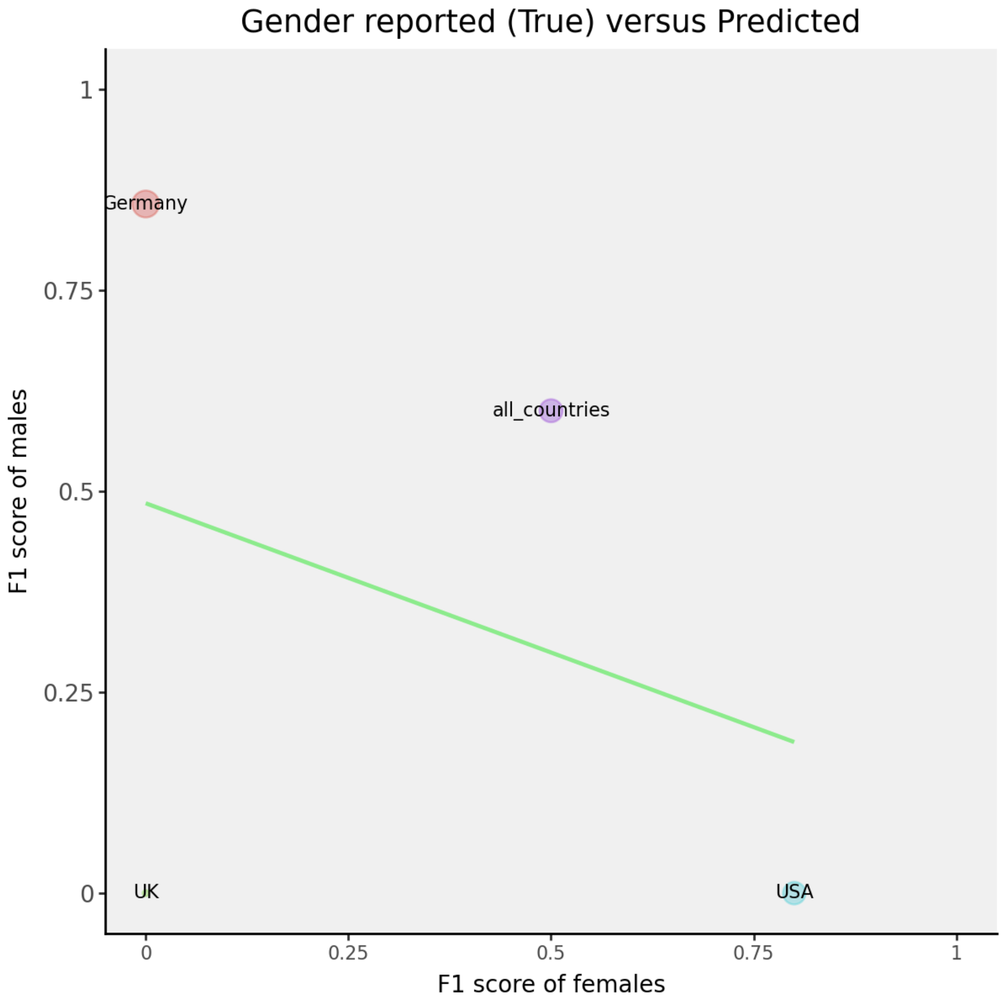
Out[ ]:

	metric	female	male	accuracy	macro avg	weighted avg	countrycode
0	precision	0.000000	1.000000	0.750000	0.500000	1.000000	Germany
1	recall	0.000000	0.750000	0.750000	0.375000	0.750000	Germany
2	f1-score	0.000000	0.857143	0.750000	0.428571	0.857143	Germany
3	support	0.000000	4.000000	0.750000	4.000000	4.000000	Germany
4	precision	0.000000	0.000000	0.000000	0.000000	0.000000	UK
5	recall	0.000000	0.000000	0.000000	0.000000	0.000000	UK
6	f1-score	0.000000	0.000000	0.000000	0.000000	0.000000	UK
7	support	1.000000	1.000000	0.000000	2.000000	2.000000	UK
8	precision	0.666667	0.000000	0.666667	0.333333	0.444444	USA
9	recall	1.000000	0.000000	0.666667	0.500000	0.666667	USA
10	f1-score	0.800000	0.000000	0.666667	0.400000	0.533333	USA
11	support	2.000000	1.000000	0.666667	3.000000	3.000000	USA
12	precision	0.400000	0.750000	0.555556	0.575000	0.633333	all_countries
13	recall	0.666667	0.500000	0.555556	0.583333	0.555556	all_countries
14	f1-score	0.500000	0.600000	0.555556	0.550000	0.566667	all_countries
15	support	3.000000	6.000000	0.555556	9.000000	9.000000	all_countries

In [ ]:

```
import plotnine as gg

(
    gg.ggplot((results_all[results_all.metric == 'f1-score']),
    gg.aes('female', 'male')
    ) +
    gg.geom_point(gg.aes(size='weighted avg', color='factor(countrycode)'), alpha=0.4) +
    gg.geom_smooth(color='lightgreen', method='lm') +
    gg.geom_text(gg.aes(label='countrycode'), size=8) +
    gg.scale_x_continuous(limits=[0,1], labels=[0, .25, 0.5, .75, 1]) +
    gg.scale_y_continuous(limits=[0,1], labels=[0, .25, 0.5, .75, 1]) +
    gg.theme_classic() +
    gg.labs(x="F1 score of females", y="F1 score of males", title='Gender reported (True) versus Pr
    gg.theme_classic() +
    gg.theme(panel_background=gg.element_rect(fill='gray', alpha=.1), legend_position='none',
             axis_text_x=gg.element_text(size=8),
             axis_text_y=gg.element_text(hjust=1, size=10),
             axis_title_x=gg.element_text(size=10),
             axis_title_y=gg.element_text(size=10),
             strip_text_x=gg.element_text(size=10),
             figure_size=(6, 6))
)
```


Gender reported (True) versus Predicted
F1 score of males
F1 score of females
1
0.75
0.5
0.25
0
0
0.25
0.5
0.75
1
Germany
all_countries
UK
USA