

analysis

September 19, 2022

1 Hanabi game – Analysis of simulation results

1.1 Data import

```
[ ]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from itertools import product
```

```
[ ]: path = "/home/nmontes/Documentos/hanabi-results/info-gain"

results = {}
results[True] = {}
results[False] = {}
player_configs = [2, 3, 4, 5]

for abd, n in product((True, False), player_configs):
    results_file = "{}/{}/summary_{}_{}_players.csv".format(path, str(abd).
↳lower(), n)
    df = pd.read_csv(results_file, sep=';', index_col="seed")

    # add efficiency as ratio score : hint
    eff = df.apply(lambda x: x.score/x.hints if x.hints > 0 else 0, axis=1)
    df.insert(df.shape[1], "efficiency", eff)

    results[abd][n] = df
```

```
[ ]: for abd, n in product((True, False), player_configs):
    print("{} players, abduction {}".format(n, abd))
    print(results[abd][n][["score", "efficiency"]].describe().loc[["mean",
↳"std"]])
    print()
```

```
2 players, abduction True
      score  efficiency
mean  18.606000    0.702015
std    5.918854    0.232094
```

	score	efficiency
mean	17.972000	0.700878
std	1.938745	0.101515

	score	efficiency
mean	16.502000	0.641741
std	1.608468	0.092351

	score	efficiency
mean	14.42200	0.615392
std	1.36955	0.086177

	score	efficiency
mean	14.568000	0.457975
std	2.930281	0.103422

	score	efficiency
mean	12.524000	0.419426
std	1.557651	0.070456

	score	efficiency
mean	11.232000	0.375438
std	1.357151	0.060059

	score	efficiency
mean	9.232000	0.331239
std	1.296742	0.060487

1.2 Summary plots

```
[ ]: plt.rcParams.update({'font.size': 28})
fig, ax = plt.subplots(figsize=(10, 10), facecolor='white')

epsilon = 0.15
lw = 3
colors = {True: 'springgreen', False: 'salmon'}

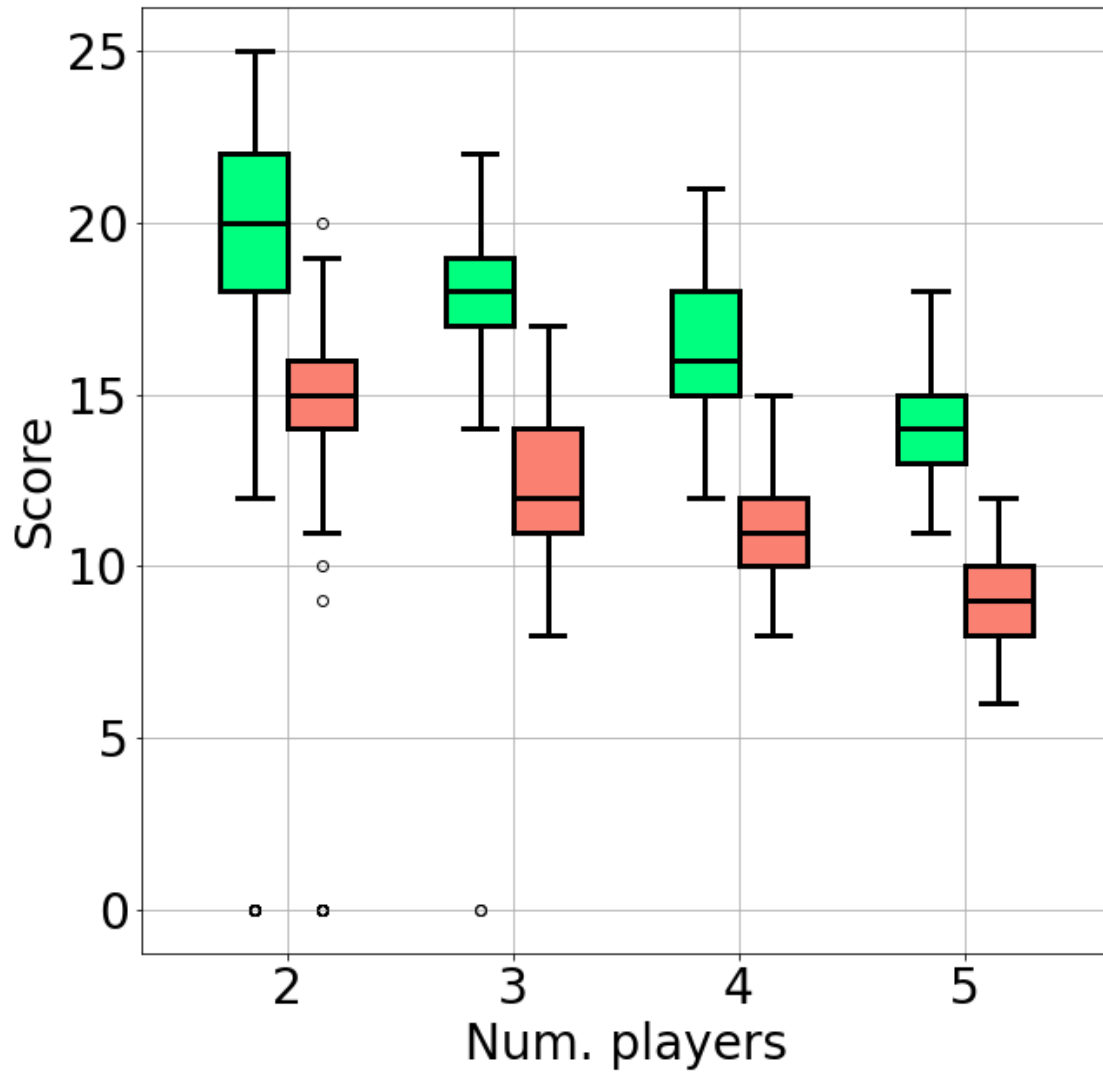
for n in player_configs:
```

```

for abd in (True, False):
    if abd:
        x = n-epsilon
    else:
        x = n+epsilon
    data = results[abd][n]["score"].to_numpy()
    bp = ax.boxplot(
        data,
        positions=[x],
        widths=[epsilon*2],
        boxprops={'linewidth': lw},
        medianprops={'linewidth': lw, 'color': 'black'},
        capprops={'linewidth': lw},
        whiskerprops={'linewidth': lw},
        patch_artist=True
    )
    for patch in bp['boxes']:
        patch.set(facecolor=colors[abd])

ax.set_xticks(player_configs, labels=player_configs)
ax.grid()
ax.set_xlabel("Num. players")
ax.set_ylabel("Score")
# plt.savefig("score.png")
plt.show()

```



```
[ ]: fig, ax = plt.subplots(figsize=(10, 10), facecolor='white')

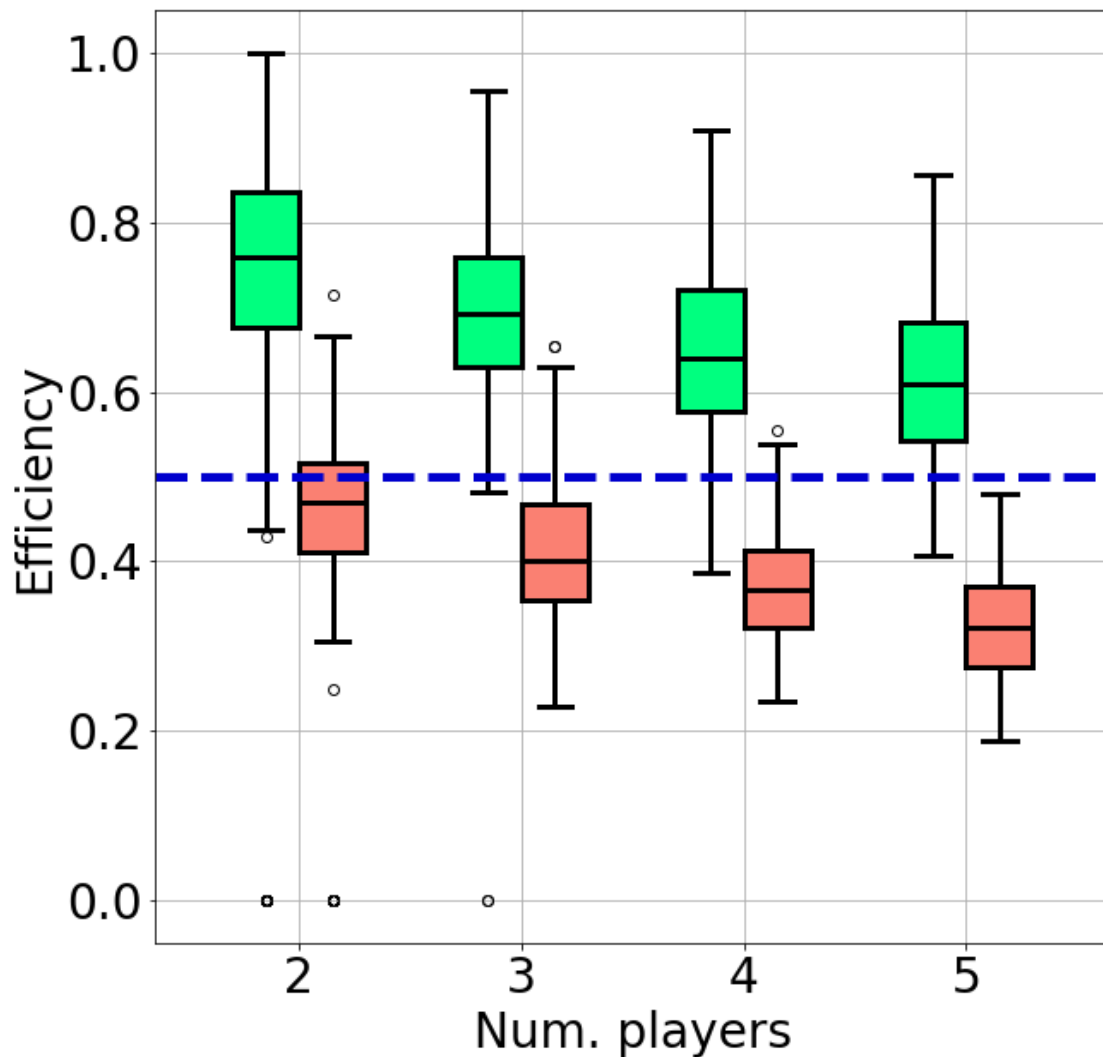
for n in player_configs:
    for abd in (True, False):
        if abd:
            x = n-epsilon
        else:
            x = n+epsilon
        data = results[abd][n]["efficiency"].to_numpy()
        bp = ax.boxplot(
            data,
            positions=[x],
            widths=[epsilon*2],
            boxprops={'linewidth': lw},
```

```

medianprops={'linewidth': lw, 'color': 'black'},
capprops={'linewidth': lw},
whiskerprops={'linewidth': lw},
patch_artist=True
)
for patch in bp['boxes']:
    patch.set(facecolor=colors[abd])

ax.set_xticks(player_configs, labels=player_configs)
ax.grid()
ax.set_xlabel("Num. players")
ax.set_ylabel("Efficiency")
ax.axhline(0.5, linewidth=5, color='mediumblue', linestyle='--')
# plt.savefig("efficiency.png")
plt.show()

```



1.3 Average information per hint

```
[ ]: for abd, n in product((True, False), player_configs):
    total_explicit_info = {}
    avg_explicit_info = {}
    if abd:
        total_implicit_info = {}
        avg_implicit_info = {}
        avg_explicit_distance = {}
        avg_implicit_distance = {}

    for seed in range(500):
        results_file = "{}info_gain_{}_{}_{}.csv".format(path, str(abd).
        ↪lower(), n, seed)
        df = pd.read_csv(results_file, sep=';')

        # compute information gain (relative to the pre-action distribution)
        # per move, aka the sum across all slots
        explicit_info_all_slots = df.groupby(["move"])["explicit_info"].sum().
        ↪replace(0, np.NaN)
        total_explicit_info[seed] = explicit_info_all_slots.sum()
        avg_explicit_info[seed] = explicit_info_all_slots.mean()
        if abd:
            implicit_info_all_slots = df.groupby(["move"])["implicit_info"].
            ↪sum().replace(0, np.NaN)
            total_implicit_info[seed] = implicit_info_all_slots.sum()
            avg_implicit_info[seed] = implicit_info_all_slots.mean()

    results[abd][n]["total_explicit_info"] = pd.Series(total_explicit_info)
    results[abd][n]["avg_explicit_info"] = pd.Series(avg_explicit_info)
    if abd:
        results[abd][n]["total_implicit_info"] = pd.Series(total_implicit_info)
        results[abd][n]["avg_implicit_info"] = pd.Series(avg_implicit_info)
```

1.4 Score rate that can be assigned to explicit and implicit information

```
[ ]: for n in player_configs:
    score = {}
    explicit_info = {}

    score_rate = {}

    results[False][n]["score_rate"] = results[False][n]["score"] /
    ↪results[False][n]["total_explicit_info"]
    score_rate['explicit'] = results[False][n]["score_rate"].mean()
```

```

    results[True][n]["score_by_expl_info"] =  $\frac{results[True][n]["total\_explicit\_info"] * score\_rate['explicit']}{results[True][n]["residual\_score"] - results[True][n]["score"]}$ 
    results[True][n]["score_by_expl_info"]

    results[True][n]["impl_score_rate"] = results[True][n]["residual_score"] /  $\frac{results[True][n]["total\_implicit\_info"]}{score\_rate['implicit']}$ 
    results[True][n]["impl_score_rate"] = results[True][n]["impl_score_rate"].replace([np.
    inf, -np.inf], np.nan).mean()

    print("{} players:".format(n))
    print("Explicit score rate: {:.2f}".format(score_rate['explicit']))
    print("Implicit score rate: {:.2f}".format(score_rate['implicit']))
    print("Ratio of implicit to explicit score rate: {:.1f}\n".
    format(score_rate['implicit']/score_rate['explicit']))

```

2 players:
 Explicit score rate: 0.70
 Implicit score rate: 1.18
 Ratio of implicit to explicit score rate: 1.7

3 players:
 Explicit score rate: 0.60
 Implicit score rate: 1.50
 Ratio of implicit to explicit score rate: 2.5

4 players:
 Explicit score rate: 0.61
 Implicit score rate: 1.32
 Ratio of implicit to explicit score rate: 2.2

5 players:
 Explicit score rate: 0.52
 Implicit score rate: 1.42
 Ratio of implicit to explicit score rate: 2.7

1.5 Statistical tests

Perform statistical tests to compare the performance metrics (score and efficiency) between the case when abduction is *off* and *on*.

```

[ ]: plt.rcParams.update({'font.size': 24})

def plot_histogram(n, variable):
    fig, ax = plt.subplots(figsize=(8, 7.5), facecolor="white")

```

```

if variable == "score":
    bins = range(0, 26)
elif variable == "efficiency":
    bins = np.linspace(0, 1, 25)
for abd in (True, False):
    x = results[abd][n][variable]
    ax.hist(x, bins, fc=colors[abd], ec="black")
locs, labels = plt.yticks()
labs = ["{:.2f}".format(i/500) for i in locs]
ax.set_yticks(locs, labels=labs)
if variable == "score":
    ax.set_xticks([0, 5, 10, 15, 20, 25])
elif variable == "efficiency":
    ax.set_xticks([0., 0.25, 0.5, 0.75, 1.])
ax.set_axisbelow(True)
ax.grid()
ax.set_xlabel(variable.capitalize())
ax.set_ylabel("Frequency")
# plt.savefig("hist_{}_{}.png".format(n, variable))
plt.show()

```

```

[ ]: from scipy import stats

# Step 1: Check that the variables are normally distributed
variables = ["score", "efficiency"]
for n, abd, var in product(player_configs, (True, False), variables):
    x = results[abd][n][var]
    _, pvalue = stats.shapiro(x)
    print("{} players, abduction {}, {}: {:.2e}".format(n, abd, var, pvalue))

```

```

2 players, abduction True, score: 1.16e-31
2 players, abduction True, efficiency: 1.62e-28
2 players, abduction False, score: 5.68e-29
2 players, abduction False, efficiency: 7.97e-23
3 players, abduction True, score: 7.00e-25
3 players, abduction True, efficiency: 5.36e-15
3 players, abduction False, score: 4.60e-10
3 players, abduction False, efficiency: 2.84e-06
4 players, abduction True, score: 5.66e-10
4 players, abduction True, efficiency: 1.38e-02
4 players, abduction False, score: 6.47e-12
4 players, abduction False, efficiency: 1.18e-07
5 players, abduction True, score: 1.41e-11
5 players, abduction True, efficiency: 1.50e-04
5 players, abduction False, score: 3.37e-13
5 players, abduction False, efficiency: 2.36e-10

```



```
[ ]: # Step 2: Pair-wise t-test
for n, var in product(player_configs, variables):
    x1 = results[True][n][var]
    x2 = results[False][n][var]
    _, pvalue = stats.ttest_rel(x1, x2)
    print("{} players, {}: {:.2e}".format(n, var, pvalue))
```

```
2 players, score: 2.62e-35
2 players, efficiency: 9.75e-72
3 players, score: 1.97e-194
3 players, efficiency: 6.26e-201
4 players, score: 1.09e-223
4 players, efficiency: 2.56e-217
5 players, score: 4.45e-232
5 players, efficiency: 3.80e-230
```

1.6 Compare distances to the *true* values

For every hint, find the *focus* slot (if there is one). Then, compare the distance of the probability distribution at the focus slot between the **post-action** distribution and the **post-explanation**

```
[ ]: distance_red = {p: [] for p in player_configs}

for n, seed in product(player_configs, range(500)):
    results_file = "{}info_gain_true_{}_{}.csv".format(path, n, seed)
    df = pd.read_csv(results_file, sep=';')
    df["delta"] = df["distance_explicit"] - df["distance_implicit"]
    df_focus = df.loc[df["delta"] > 0.]
    percentage_reduction = (df_focus["distance_explicit"] -
df_focus["distance_implicit"]) / df_focus["distance_explicit"] * 100
    distance_red[n].append(percentage_reduction.mean())
```

```
[ ]: print("Percentage gain in distance to the ground truth:")
for p in player_configs:
    print("{} players: {:.2f}%".format(p, np.nanmean(distance_red[p])))
```

```
Percentage gain in distance to the ground truth:
2 players: 85.33%
3 players: 88.29%
4 players: 89.43%
5 players: 91.49%
```