# experimentacion

May 31, 2023

[ ]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from typing import List, Tuple
from random import random
from tqdm import tqdm
import seaborn as sns

#!pip3 install tabulate
# Tabulate es una libreria para imprimir tablas en consola, habilita df.
↪to_markdown() para incluir las tablas en el informe
```

Experimentación. Realizar experimentos sobre todas las instancias comparando el modelo propuesto respecto al de la solución actual de la compañía. En cada caso, medir la mejora porcentual obtenida. Sean $z_b$ y $z_g$ el valor de la función objetivo de una solución del modelo para el batching y el de FCFS, respectivamente. definimos la mejora relativa como

$$\%\text{gap} = \frac{z_g - z_b}{z_b}$$

En caso de considerarlo conveniente, pueden agregar otras métricas complementarias (respecto al método o a las soluciones) para el análisis de los resultados. Sugerencia: se recomienda sistematizar la realización de experimentos, idealmente definiendo la lista de instancias a considerar y reportando en algún formato conveniente (por ejemplo, csv) el resumen de los resultados obtenidos, para ser analizados posteriormente.

[ ]:
```python
solutions = pd.read_csv('../output/results.csv')

"Columnas: " + ' | '.join(list(solutions.columns))
```

[ ]:
```
'Columnas: filename | n | greedy_cost | min_cost_flow_cost | greedy_time |
min_cost_flow_time | priority_cost | priority_time'
```

[ ]:
```python
solutions["gap"] = (solutions["greedy_cost"] - solutions["min_cost_flow_cost"])␣
↪/ solutions["min_cost_flow_cost"]
solutions.head()
```

[ ]:

```
             filename   n  greedy_cost  min_cost_flow_cost  greedy_time  \
0  input/small_0.csv  10         36.9                29.3     0.003834
1  input/small_1.csv  10         42.4                32.4     0.003625
2  input/small_2.csv  10         65.6                56.9     0.003375
3  input/small_3.csv  10         29.5                23.7     0.004042
4  input/small_4.csv  10         33.9                30.8     0.003750

   min_cost_flow_time  priority_cost  priority_time       gap
0            1.278210           30.0       0.072542  0.259386
1            0.066792           33.0       0.051625  0.308642
2            0.080667           62.7       0.074875  0.152900
3            0.082041           24.4       0.074625  0.244726
4            0.085584           32.2       0.069042  0.100649
```

[ ]:

```python
# ignore the reg_log column
solutions.describe()
```

[ ]:

```
                n  greedy_cost  min_cost_flow_cost  greedy_time  \
count   40.000000    40.000000           40.000000    40.000000
mean   215.000000   696.782500          587.277500     0.466245
std    187.903412   583.800751          498.484705     0.579288
min     10.000000    29.500000           23.700000     0.003375
25%     77.500000   219.875000          184.925000     0.046980
50%    175.000000   572.800000          471.850000     0.227646
75%    312.500000  1088.700000          912.875000     0.605584
max    500.000000  1737.400000         1521.800000     1.826960

       min_cost_flow_time  priority_cost  priority_time        gap
count           40.000000      40.000000      40.000000  40.000000
mean            24.306557     630.085000      31.161884   0.191644
std             31.888349     530.187328      42.366877   0.059078
min              0.063666      24.400000       0.051625   0.073239
25%              1.937993     200.475000       1.638575   0.154794
50%              9.322780     520.450000       9.647795   0.178846
75%             30.937775     991.000000      39.802275   0.241455
max             98.613500    1627.800000     137.926000   0.308642
```

[ ]:

```python
# output as latex table
#print(solutions.drop(columns=['priority_time', 'priority_cost']).describe().
↪to_markdown())
solutions.drop(columns=['priority_time', 'priority_cost']).describe()
```

[ ]:

```
                n  greedy_cost  min_cost_flow_cost  greedy_time  \
count   40.000000    40.000000           40.000000    40.000000
mean   215.000000   696.782500          587.277500     0.466245
std    187.903412   583.800751          498.484705     0.579288
min     10.000000    29.500000           23.700000     0.003375
```

```
25%     77.500000   219.875000          184.925000     0.046980
50%    175.000000   572.800000          471.850000     0.227646
75%    312.500000  1088.700000          912.875000     0.605584
max    500.000000  1737.400000         1521.800000     1.826960

       min_cost_flow_time        gap
count           40.000000  40.000000
mean            24.306557   0.191644
std             31.888349   0.059078
min              0.063666   0.073239
25%              1.937993   0.154794
50%              9.322780   0.178846
75%             30.937775   0.241455
max             98.613500   0.308642
```

[ ]:
```
#print(solutions.drop(columns=['gap', 'priority_cost', 'priority_time']).
↪describe().to_markdown())
solutions.drop(columns=['gap', 'priority_cost', 'priority_time']).describe()
```

[ ]:
```
                n  greedy_cost  min_cost_flow_cost  greedy_time  \
count   40.000000    40.000000           40.000000    40.000000
mean   215.000000   696.782500          587.277500     0.466245
std    187.903412   583.800751          498.484705     0.579288
min     10.000000    29.500000           23.700000     0.003375
25%     77.500000   219.875000          184.925000     0.046980
50%    175.000000   572.800000          471.850000     0.227646
75%    312.500000  1088.700000          912.875000     0.605584
max    500.000000  1737.400000         1521.800000     1.826960

       min_cost_flow_time
count           40.000000
mean            24.306557
std             31.888349
min              0.063666
25%              1.937993
50%              9.322780
75%             30.937775
max             98.613500
```

[ ]:
```
gaps = solutions[['n', 'gap', "greedy_cost", "min_cost_flow_cost"]]
#print(gaps.groupby('n')[["greedy_cost", "min_cost_flow_cost", 'gap']].mean().
↪to_markdown())
gaps.groupby('n')[["greedy_cost", "min_cost_flow_cost", 'gap']].mean()
```

[ ]:
```
     greedy_cost  min_cost_flow_cost       gap
n
10         46.93               40.06  0.177322
```

```
100       337.31               280.63  0.205883
250       849.60               701.60  0.212157
500      1553.29              1326.82  0.171215
```

[ ]:
```
#print(gaps.groupby('n')['gap'].describe().to_markdown())
gaps.groupby('n')['gap'].describe()
```

[ ]:
```
     count      mean       std       min       25%       50%       75%  \
n
10    10.0  0.177322  0.076926  0.073239  0.113712  0.169066  0.233651
100   10.0  0.205883  0.057421  0.104009  0.171945  0.194773  0.249033
250   10.0  0.212157  0.059926  0.144362  0.157622  0.201565  0.267717
500   10.0  0.171215  0.030561  0.135713  0.143316  0.170003  0.198171

          max
n
10   0.308642
100  0.287764
250  0.299222
500  0.216486
```

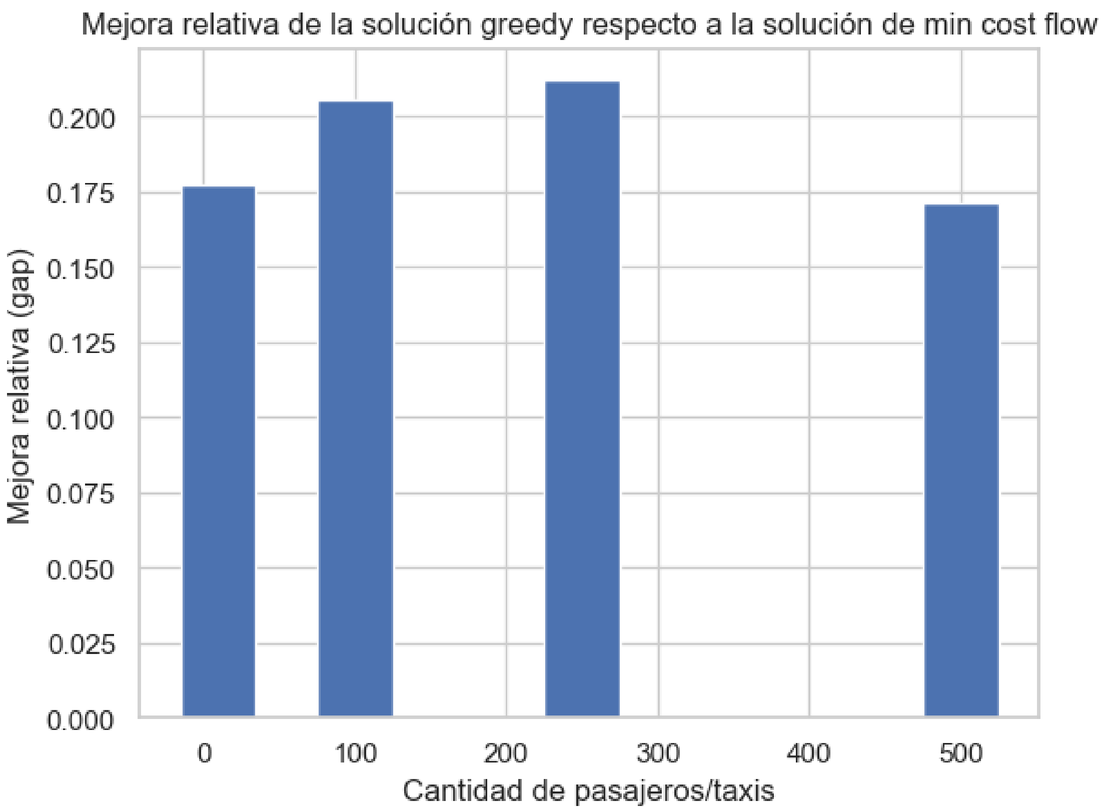
[ ]:
```
avg_gap = solutions["gap"].mean()
avg_gap
```

[ ]:
```
0.19164428484224535
```

[ ]:
```
!mkdir ../output/figures
```

[ ]:
```
# Plot gap avg vs. n

avg_10  = solutions[solutions["n"] == 10]["gap"].mean()
avg_100 = solutions[solutions["n"] == 100]["gap"].mean()
avg_250 = solutions[solutions["n"] == 250]["gap"].mean()
avg_500 = solutions[solutions["n"] == 500]["gap"].mean()

# Plot gap avg vs. n
# Bar plot

ns = [10, 100, 250, 500]
avg_gaps = [avg_10, avg_100, avg_250, avg_500]

plt.bar(ns, avg_gaps, width=50)
plt.xlabel("Cantidad de pasajeros/taxis")
plt.ylabel("Mejora relativa (gap)")
plt.title("Mejora relativa de la solución greedy respecto a la solución de min␣
 ↪cost flow")
```

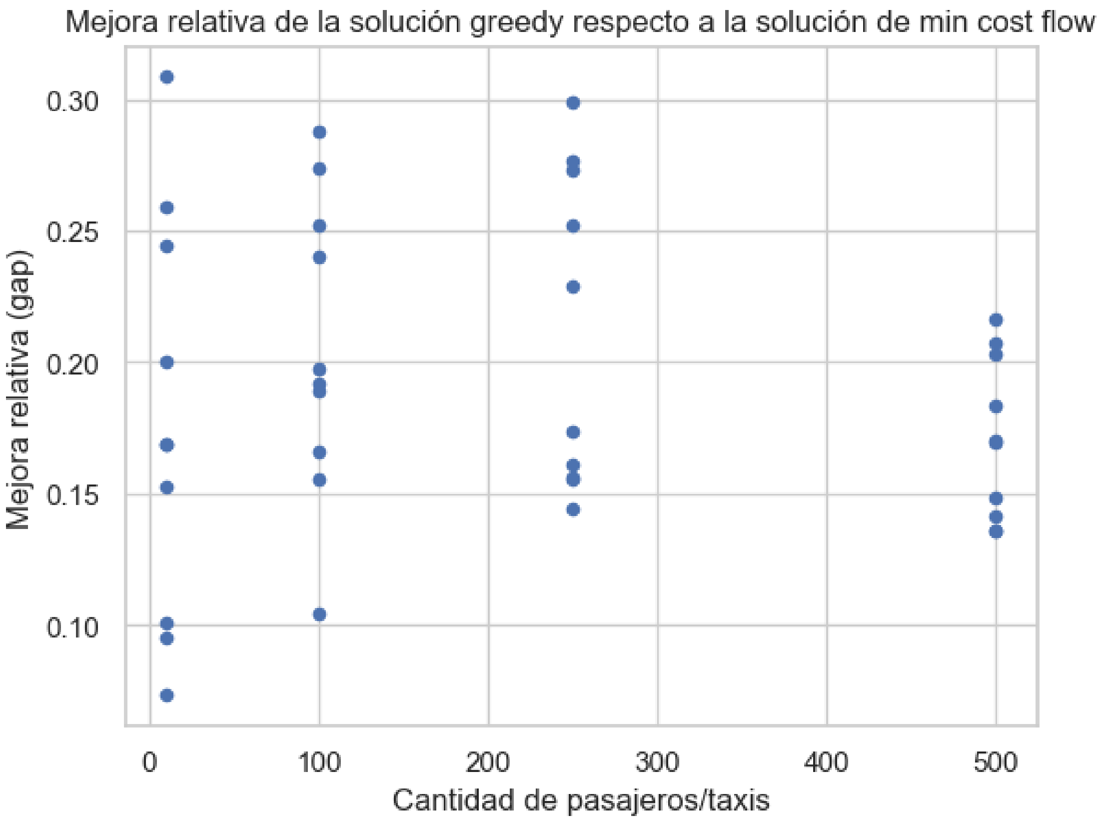
```
plt.savefig("../output/figures/greedy_vs_batching.png")

plt.show()
```



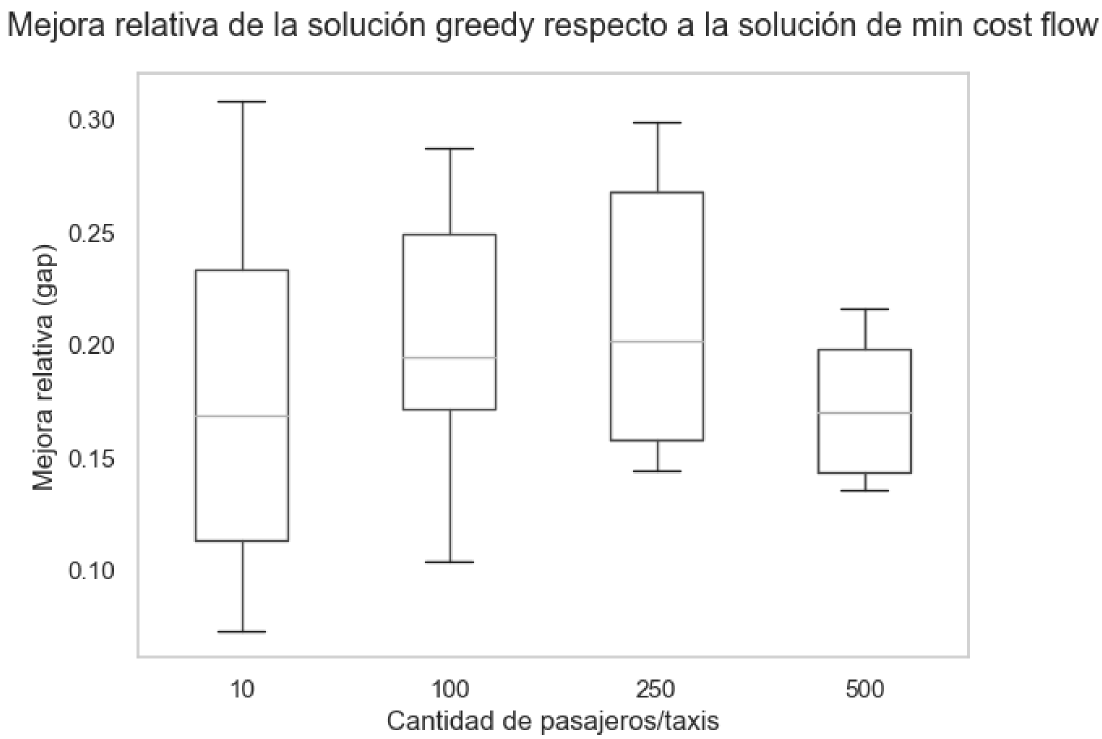

[ ]:
```
fig, ax = plt.subplots()

_ = solutions.plot.scatter(x="n", y="gap",
    title="Mejora relativa de la solución greedy respecto a la solución de min␣
 ↪cost flow",
    ax=ax
)

ax.set_xlabel("Cantidad de pasajeros/taxis")
ax.set_ylabel("Mejora relativa (gap)")

plt.savefig("../output/figures/greedy_vs_batching_scatter.png")
```

```
/Users/nacho/opt/anaconda3/envs/coding/lib/python3.8/site-
packages/pandas/plotting/_matplotlib/core.py:1114: UserWarning: No data for
```

```
colormapping provided via 'c'. Parameters 'cmap' will be ignored
  scatter = ax.scatter(
```



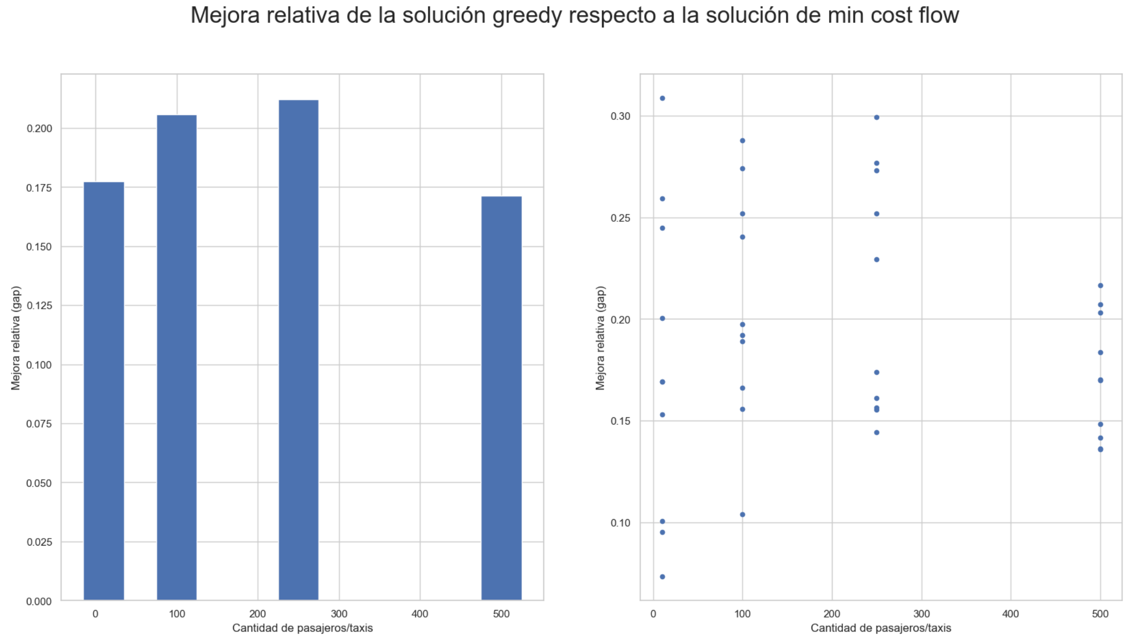

```
[ ]: fig, ax = plt.subplots()

# Boxplot
solutions.boxplot(column="gap", by="n", ax=ax,
    grid=False
)

#ax.set_title("Mejora relativa de la solución greedy respecto a la solución de␣
 ↪min cost flow")
ax.set_title("")
ax.set_xlabel("Cantidad de pasajeros/taxis")
ax.set_ylabel("Mejora relativa (gap)")

fig.suptitle("Mejora relativa de la solución greedy respecto a la solución de␣
 ↪min cost flow")

plt.savefig("../output/figures/greedy_vs_batching_boxplot.png")
```




```
[ ]: fig, axs = plt.subplots(1, 2, figsize=(20, 10))

axs[0].bar(ns, avg_gaps, width=50)
axs[0].set_xlabel("Cantidad de pasajeros/taxis")
axs[0].set_ylabel("Mejora relativa (gap)")
# axs[0].set_title("Mejora relativa de la solución greedy respecto a la␣
 ↪solución de min cost flow")

_ = solutions.plot.scatter(x="n", y="gap",
    # title="Mejora relativa de la solución greedy respecto a la solución de␣
 ↪min cost flow",
    ax=axs[1]
)

axs[1].set_xlabel("Cantidad de pasajeros/taxis")
axs[1].set_ylabel("Mejora relativa (gap)")

fig.suptitle("Mejora relativa de la solución greedy respecto a la solución de␣
 ↪min cost flow", fontsize=24)

plt.savefig("../output/figures/greedy_vs_batching_scatter_and_bar.png")
```

/Users/nacho/opt/anaconda3/envs/coding/lib/python3.8/site-

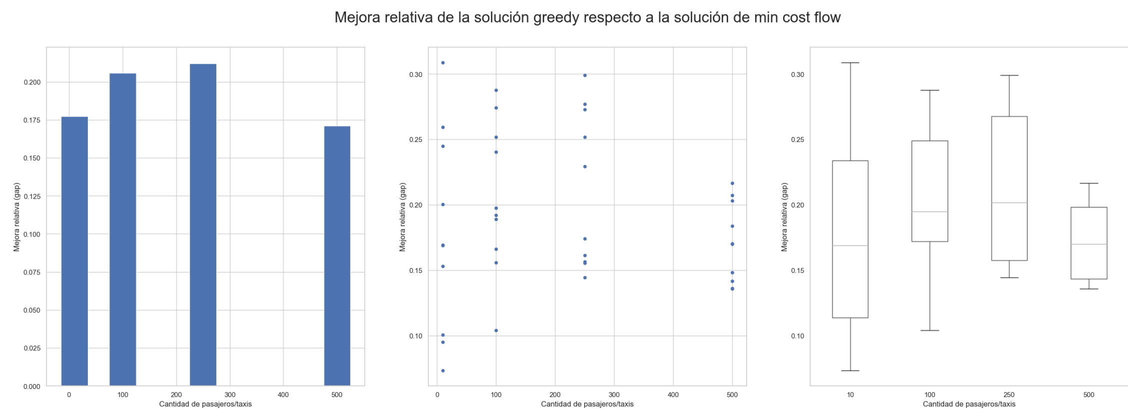
```
packages/pandas/plotting/_matplotlib/core.py:1114: UserWarning: No data for
colormapping provided via 'c'. Parameters 'cmap' will be ignored
  scatter = ax.scatter(
```




```
[ ]: fig, axs = plt.subplots(1, 3, figsize=(30, 10))

axs[0].bar(ns, avg_gaps, width=50)
axs[0].set_xlabel("Cantidad de pasajeros/taxis")
axs[0].set_ylabel("Mejora relativa (gap)")
# axs[0].set_title("Mejora relativa de la solución greedy respecto a la␣
 ↪solución de min cost flow")

_ = solutions.plot.scatter(x="n", y="gap",
    ax=axs[1]
)
axs[1].set_xlabel("Cantidad de pasajeros/taxis")
axs[1].set_ylabel("Mejora relativa (gap)")

solutions.boxplot(column="gap", by="n", ax=axs[2],
    grid=False
)

#ax.set_title("Mejora relativa de la solución greedy respecto a la solución de␣
 ↪min cost flow")
axs[2].set_title("")
axs[2].set_xlabel("Cantidad de pasajeros/taxis")
```

```
axs[2].set_ylabel("Mejora relativa (gap)")

fig.suptitle("Mejora relativa de la solución greedy respecto a la solución de␣
↪min cost flow", fontsize=24)

plt.savefig("../output/figures/greedy_vs_batching_scatter_bar_box.png")
```

```
/Users/nacho/opt/anaconda3/envs/coding/lib/python3.8/site-
packages/pandas/plotting/_matplotlib/core.py:1114: UserWarning: No data for
colormapping provided via 'c'. Parameters 'cmap' will be ignored
  scatter = ax.scatter(
```




## 0.1 Idea: Generar instancias de prueba aleatorias

Generar 10 instancias de prueba para cada n con n entre [0, 500].

Una instancia de prueba es un csv de la forma:

- En la primera línea, el número de taxis/pasajeros $n$.
- Entre la fila 2 y $n+1$, las coordenadas de los taxis.
- Entre la fila $n+2$ y $2n+1$, las coordenadas de los pasajeros, la distancia de su viaje, el costo del viaje.
- Entre la fila $2n+2$ y $3n+1$, la matriz de distancias entre taxis y pasajeros.

Generar una instancia de prueba es generar un csv de la forma anterior.

Ejemplo para $n = 10$:

[ ]:
```
n = 10

# taxis
taxis : List[Tuple[int]]= [(random() * 100, random() * 100) for _ in range(n)]

# pasajeros
```

```
pasajeros : List[Tuple[int]] = [(random() * 100, random() * 100, random() *␣
↪100, random() * 100) for _ in range(n)]

# matriz de distancias
# Formula para calcular la distancia entre dos puntos (x1, y1) y (x2, y2):
# sqrt((x1 - x2)^2 + (y1 - y2)^2)

distancias : List[List[float]] = []

for i in range(n):
    distancias.append([])
    for j in range(n):
        distancias[i].append(((taxis[i][0] - pasajeros[j][0]) ** 2 +␣
↪(taxis[i][1] - pasajeros[j][1]) ** 2) ** 0.5)

# Guardar en ../input/fake_instances/small_test.csv

with open('../input/fake_instances/small_test_5000.csv', 'w') as f:
    f.write(str(n) + '\n')
    for i in range(n):
        f.write(str(taxis[i][0]) + ',' + str(taxis[i][1]) + '\n')
    for i in range(n):
        f.write(str(pasajeros[i][0]) + ',' + str(pasajeros[i][1]) + ',' +␣
↪str(pasajeros[i][2]) + ',' + str(pasajeros[i][3]) + '\n')
    for i in range(n):
        for j in range(n):
            f.write(str(distancias[i][j]) + ',')
        f.write('\n')
```

[ ]:
```
def generate_instance(n: int):
    # taxis
    taxis : List[Tuple[int]]= [(random() * 100, random() * 100) for _ in␣
↪range(n)]

    # pasajeros
    pasajeros : List[Tuple[int]] = [(random() * 100, random() * 100, random() *␣
↪100, random() * 100) for _ in range(n)]

    # matriz de distancias
    # Formula para calcular la distancia entre dos puntos (x1, y1) y (x2, y2):
    # sqrt((x1 - x2)^2 + (y1 - y2)^2)

    distancias : List[List[float]] = []

    for i in range(n):
        distancias.append([])
        for j in range(n):
```

```
            distancias[i].append(((taxis[i][0] - pasajeros[j][0]) ** 2 +
 ↪(taxis[i][1] - pasajeros[j][1]) ** 2) ** 0.5)

    return taxis, pasajeros, distancias

def write_csv(n, taxis, pasajeros, distancias,  k=None):

    with open('../input/fake_instances/batched/' + str(n) + '/xxl_fake_' +
 ↪str(k) + '.csv', 'w') as f:
        f.write(str(n) + '\n')
        for i in range(n):
            f.write(str(taxis[i][0]) + ',' + str(taxis[i][1]) + '\n')
        for i in range(n):
            f.write(str(pasajeros[i][0]) + ',' + str(pasajeros[i][1]) + ',' +
 ↪str(pasajeros[i][2]) + ',' + str(pasajeros[i][3]) + '\n')
        for i in range(n):
            for j in range(n):
                f.write(str(distancias[i][j]) + ',')
            f.write('\n')
```

[ ]:
```
# Generar 10 instancias de prueba para cada n en [2, 500]
for n in tqdm(range(2, 501)):
    for i in range(1):
        taxis, pasajeros, distancias = generate_instance(n)
        write_csv(n, taxis, pasajeros, distancias)
```

[ ]:
```
!mkdir ../input/fake_instances
```

[ ]:
```
!rm -rf ../input/fake_instances && mkdir ../input/fake_instances
```

[ ]:
```
from multiprocess import Pool
import os
```

[ ]:
```
# Paralelizar el código anterior

with Pool(10) as p:
    instances = p.map(generate_instance, range(2, 501))
    for j in range(10):
        for n, (taxis, pasajeros, distancias) in enumerate(tqdm(instances)):
            write_csv(n, taxis, pasajeros, distancias, j)
```

## 0.2 Experimentación sobre instancias de prueba

[ ]:
```
ad_hoc_solutions = pd.read_csv("../output/fake/results.csv")
ad_hoc_solutions.head()
```

```
[ ]:                         filename    n  greedy_cost  min_cost_flow_cost  \
0  input/fake_instances/fake_403_6.csv  403      2587.86            1922.110
1   input/fake_instances/fake_78_1.csv   78      1265.03             943.192
2  input/fake_instances/fake_446_6.csv  446      3304.80            2196.170
3  input/fake_instances/fake_460_5.csv  460      3487.10            2259.200
4  input/fake_instances/fake_398_9.csv  398      3613.14            2578.070

   greedy_time  min_cost_flow_time  priority_cost  priority_time
0     0.658875            41.68110       2054.340       50.36580
1     0.038583             1.29067        994.488        1.44458
2     0.780417            52.30880       2390.200       45.54520
3     0.784416            48.57390       2518.440       51.50390
4     0.667834            41.68870       2828.010       38.68040
```

```
[ ]: ad_hoc_solutions = ad_hoc_solutions[ad_hoc_solutions["n"] > 2]
```

```
[ ]: #solutions["gap"] = (solutions["greedy_cost"] -␣
      ↪solutions["min_cost_flow_cost"]) / solutions["min_cost_flow_cost"]
     ad_hoc_solutions["gap"] = (ad_hoc_solutions["greedy_cost"] -␣
      ↪ad_hoc_solutions["min_cost_flow_cost"]) /␣
      ↪ad_hoc_solutions["min_cost_flow_cost"]
     ad_hoc_solutions.head()
```

```
[ ]:                         filename    n  greedy_cost  min_cost_flow_cost  \
0  input/fake_instances/fake_403_6.csv  403      2587.86            1922.110
1   input/fake_instances/fake_78_1.csv   78      1265.03             943.192
2  input/fake_instances/fake_446_6.csv  446      3304.80            2196.170
3  input/fake_instances/fake_460_5.csv  460      3487.10            2259.200
4  input/fake_instances/fake_398_9.csv  398      3613.14            2578.070

   greedy_time  min_cost_flow_time  priority_cost  priority_time  batch  \
0     0.658875            41.68110       2054.340       50.36580     40
1     0.038583             1.29067        994.488        1.44458      7
2     0.780417            52.30880       2390.200       45.54520     44
3     0.784416            48.57390       2518.440       51.50390     46
4     0.667834            41.68870       2828.010       38.68040     39

        gap
0  0.346364
1  0.341222
2  0.504802
3  0.543511
4  0.401490
```

```
[ ]: ad_hoc_solutions["gap"].describe()
```

```
[ ]: count    4960.000000
     mean        0.417210
     std         0.097456
     min         0.058418
     25%         0.366200
     50%         0.427162
     75%         0.483098
     max         0.772146
     Name: gap, dtype: float64
```

```
[ ]: ad_hoc_solutions.groupby("n")["gap"].describe()
     #print(ad_hoc_solutions.groupby("n")["gap"].describe().to_markdown())
```

```
[ ]:      count      mean           std       min       25%       50%       75%  \
     n
     3     10.0  0.335435  0.000000e+00  0.335435  0.335435  0.335435  0.335435
     4     10.0  0.772146  0.000000e+00  0.772146  0.772146  0.772146  0.772146
     5     10.0  0.088242  0.000000e+00  0.088242  0.088242  0.088242  0.088242
     6     10.0  0.157427  2.925695e-17  0.157427  0.157427  0.157427  0.157427
     7     10.0  0.202027  2.925695e-17  0.202027  0.202027  0.202027  0.202027
     ..     …       …           …          …         …         …         …
     494   10.0  0.433143  5.851389e-17  0.433143  0.433143  0.433143  0.433143
     495   10.0  0.578101  0.000000e+00  0.578101  0.578101  0.578101  0.578101
     496   10.0  0.464340  0.000000e+00  0.464340  0.464340  0.464340  0.464340
     497   10.0  0.538973  0.000000e+00  0.538973  0.538973  0.538973  0.538973
     498   10.0  0.476677  0.000000e+00  0.476677  0.476677  0.476677  0.476677

               max
     n
     3    0.335435
     4    0.772146
     5    0.088242
     6    0.157427
     7    0.202027
     ..        …
     494  0.433143
     495  0.578101
     496  0.464340
     497  0.538973
     498  0.476677

     [496 rows x 8 columns]
```

```
[ ]: # ad_hoc_solutions.groupby("n")["gap"].describe()
     # Get values every 50
```

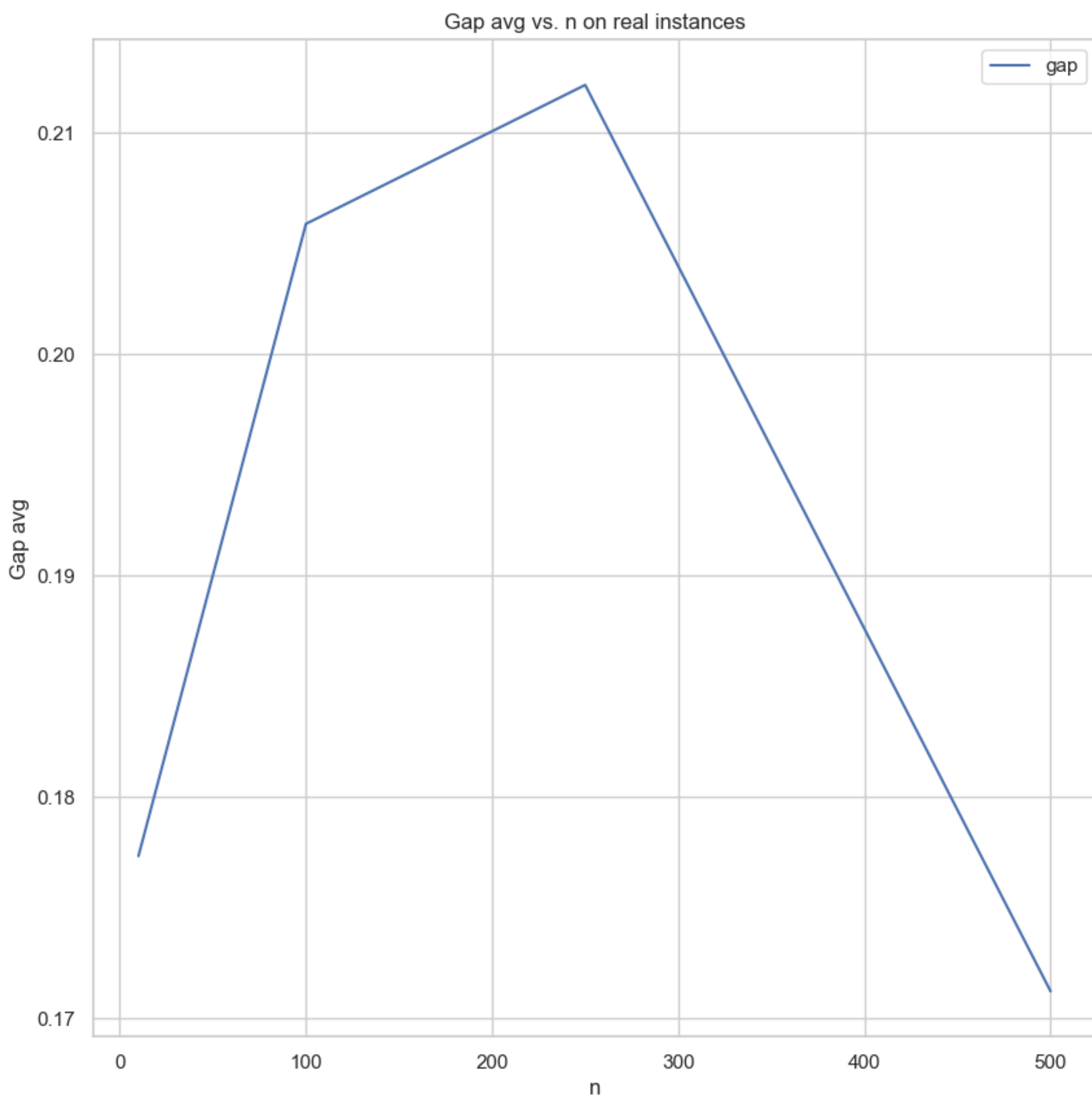
```
mean_res = ad_hoc_solutions[(ad_hoc_solutions["n"] % 50 == 0) |␣
 ↪(ad_hoc_solutions["n"] == 498) | (ad_hoc_solutions["n"] == 3)].
 ↪groupby("n")["gap"].describe()
mean_res.drop(columns=["count", "min", "max", "25%", "50%", "75%", "std"])
#print(mean_res.drop(columns=["count", "min", "max", "25%", "50%", "75%",␣
 ↪"std"]).to_markdown())
```

[ ]:

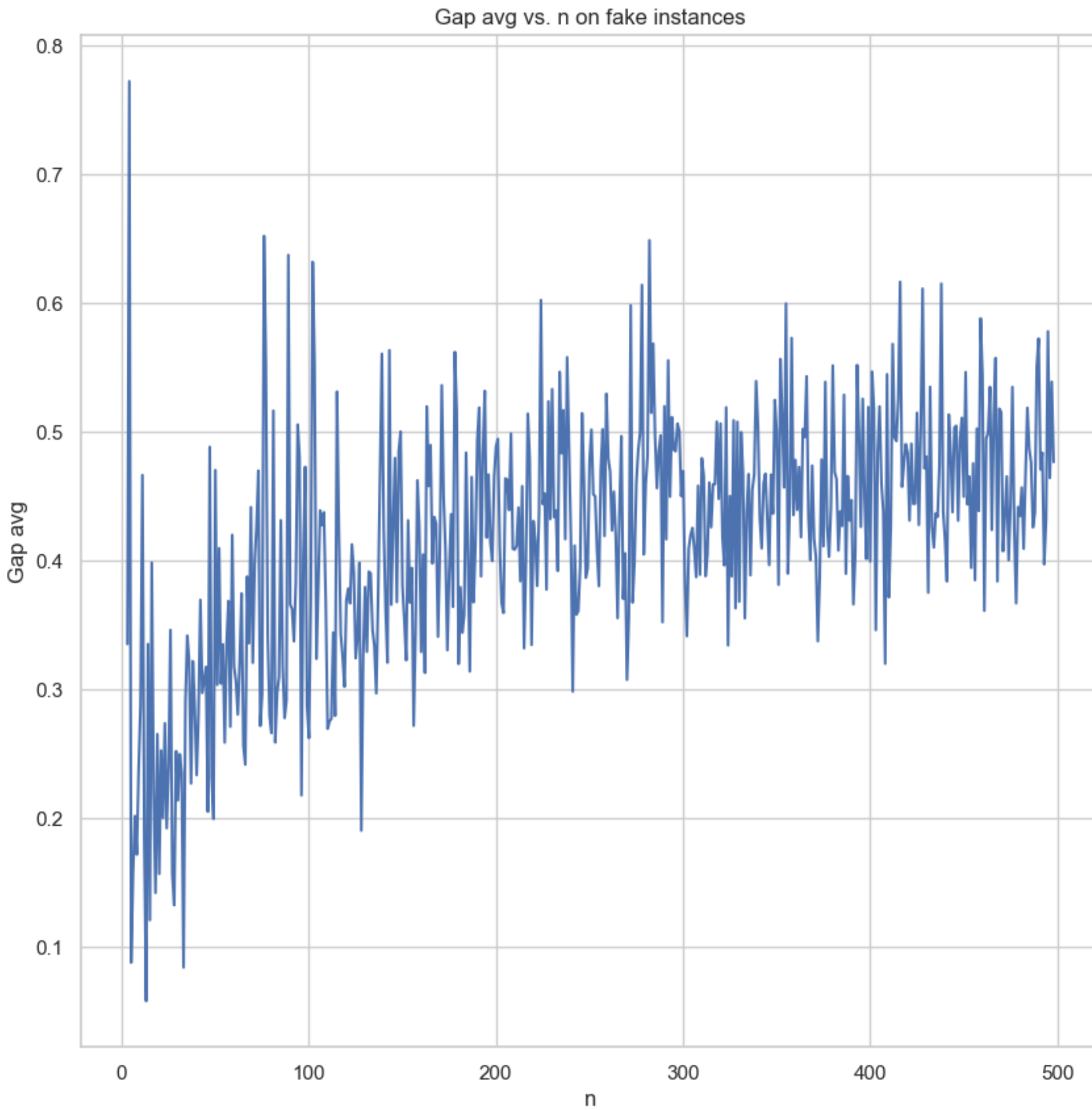
```
         mean
n
3    0.335435
50   0.470381
100  0.262508
150  0.380710
200  0.488713
250  0.477224
300  0.469546
350  0.500416
400  0.399574
450  0.449788
498  0.476677
```

[ ]:

```
fig, ax = plt.subplots(figsize=(10, 10))
solutions.groupby("n")[["gap"]].mean().plot(ax=ax)

ax.set_title("Gap avg vs. n on real instances")

ax.set_xlabel("n")
ax.set_ylabel("Gap avg")

plt.savefig("../output/figures/gap_avg_vs_n_real.png")
```



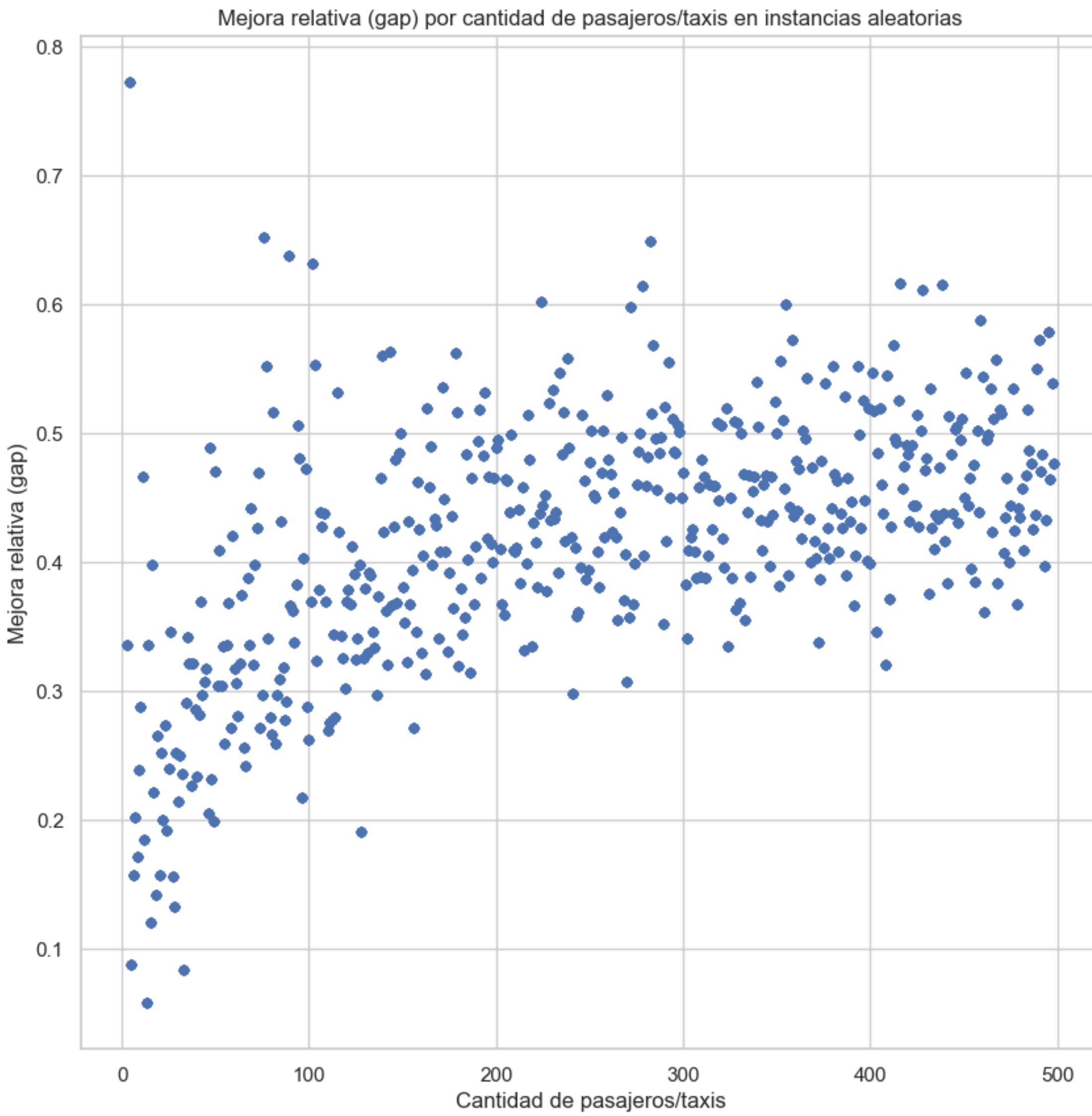

```
[ ]: # Plot gap avg vs. n
fig, ax = plt.subplots(figsize=(10, 10))

ad_hoc_solutions.groupby("n")["gap"].mean().plot(ax=ax)

ax.set_title("Gap avg vs. n on fake instances")
ax.set_xlabel("n")
ax.set_ylabel("Gap avg")

plt.savefig("../output/figures/gap_avg_vs_n_fake.png")
```




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


ad_hoc_solutions.plot.scatter(
    x="n", y="gap",
    title="Mejora relativa (gap) por cantidad de pasajeros/taxis en instancias␣
 ↪aleatorias",
    ax=ax
)
```

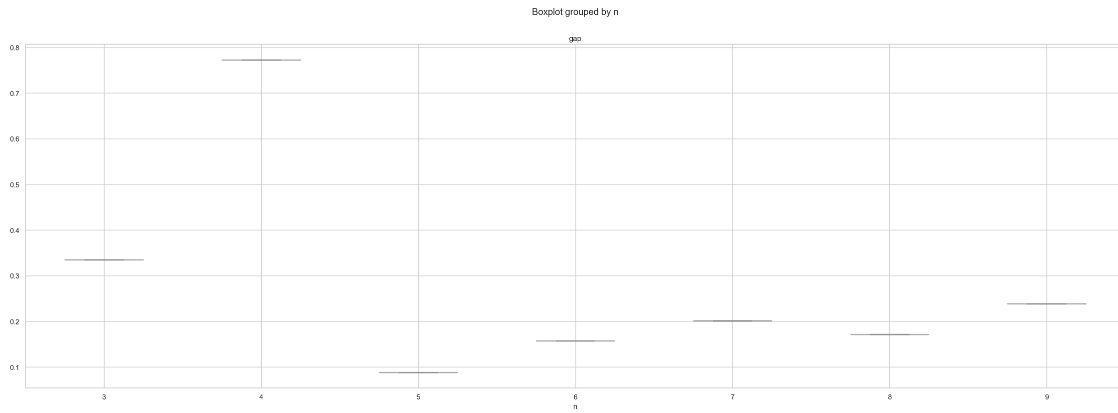
```
ax.set_xlabel("Cantidad de pasajeros/taxis")
ax.set_ylabel("Mejora relativa (gap)")

plt.savefig("../output/figures/gap_vs_n_fake_scatter.png")
```

```
/Users/nacho/opt/anaconda3/envs/coding/lib/python3.8/site-
packages/pandas/plotting/_matplotlib/core.py:1114: UserWarning: No data for
colormapping provided via 'c'. Parameters 'cmap' will be ignored
  scatter = ax.scatter(
```



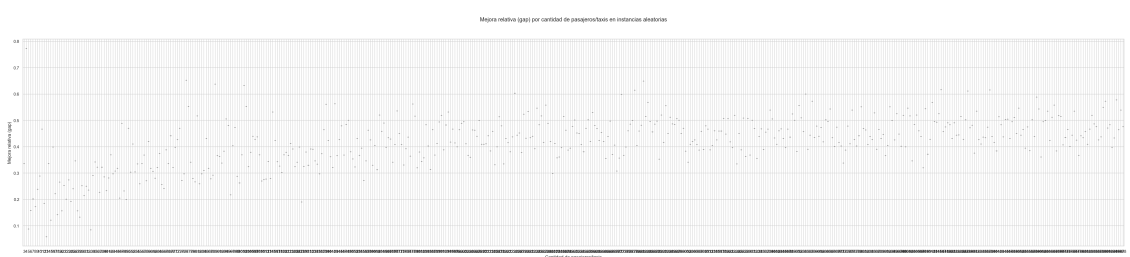

[ ]:
```
ad_hoc_solutions[ad_hoc_solutions["n"] < 10].boxplot(column="gap", by="n",␣
↪figsize=(30, 10))
```

[ ]: <Axes: title={'center': 'gap'}, xlabel='n'>




[ ]:
```
fig, ax = plt.subplots(figsize=(50, 10))

#boxplot

ad_hoc_solutions.boxplot(column="gap", by="n", ax=ax)

ax.set_title("")
ax.set_xlabel("Cantidad de pasajeros/taxis")
ax.set_ylabel("Mejora relativa (gap)")

fig.suptitle("Mejora relativa (gap) por cantidad de pasajeros/taxis en␣
 ↪instancias aleatorias")

#plt.savefig("../output/figures/gap_vs_n_fake_scatter.png")
```

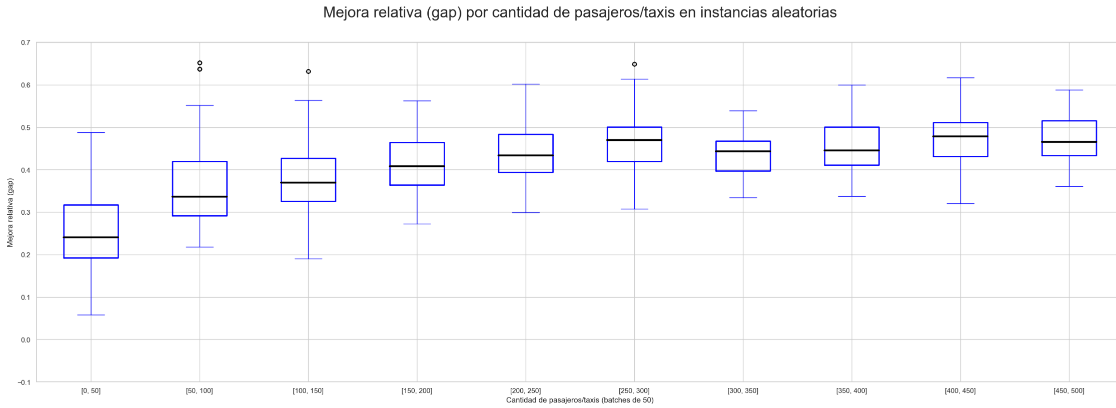
[ ]: Text(0.5, 0.98, 'Mejora relativa (gap) por cantidad de pasajeros/taxis en instancias aleatorias')



[ ]:
```
[str(i * 50) for i in range(1, 10)]
```

[ ]: ['50', '100', '150', '200', '250', '300', '350', '400', '450']

[ ]:
```
fig, ax = plt.subplots(figsize=(30, 10))

#boxplot

#ad_hoc_solutions.boxplot(column="gap", by="n", ax=ax)

# Batch ad_hoc_solutions n in batches of 50

ad_hoc_solutions["n_batch"] = ad_hoc_solutions["n"] // 50

ad_hoc_solutions.boxplot(
    column="gap",
    by="n_batch",
    ax=ax,
    color="blue",
    boxprops=dict(linestyle='-', linewidth=2, color="blue"),
    medianprops=dict(linestyle='-', linewidth=3, color="black"),
)

#ax.set_title("Mejora relativa (gap) por cantidad de pasajeros/taxis en␣
↪instancias aleatorias")
ax.set_title("")
ax.set_xlabel("Cantidad de pasajeros/taxis (batches de 50)")
ax.set_ylabel("Mejora relativa (gap)")

# Replace xticks to be the batch number intervals of 50 (0, 50, 100, 150, ...)
# Without affecting the scale of the plot

ax.set_xticklabels([f"[{i*50}, {(i+1)*50}]"  for i in range(0, 10)])

ax.set_ylim(-0.1, 0.7)

fig.suptitle("Mejora relativa (gap) por cantidad de pasajeros/taxis en␣
↪instancias aleatorias", fontsize=24)

plt.savefig("../output/figures/gap_vs_n_fake_box.png")
```

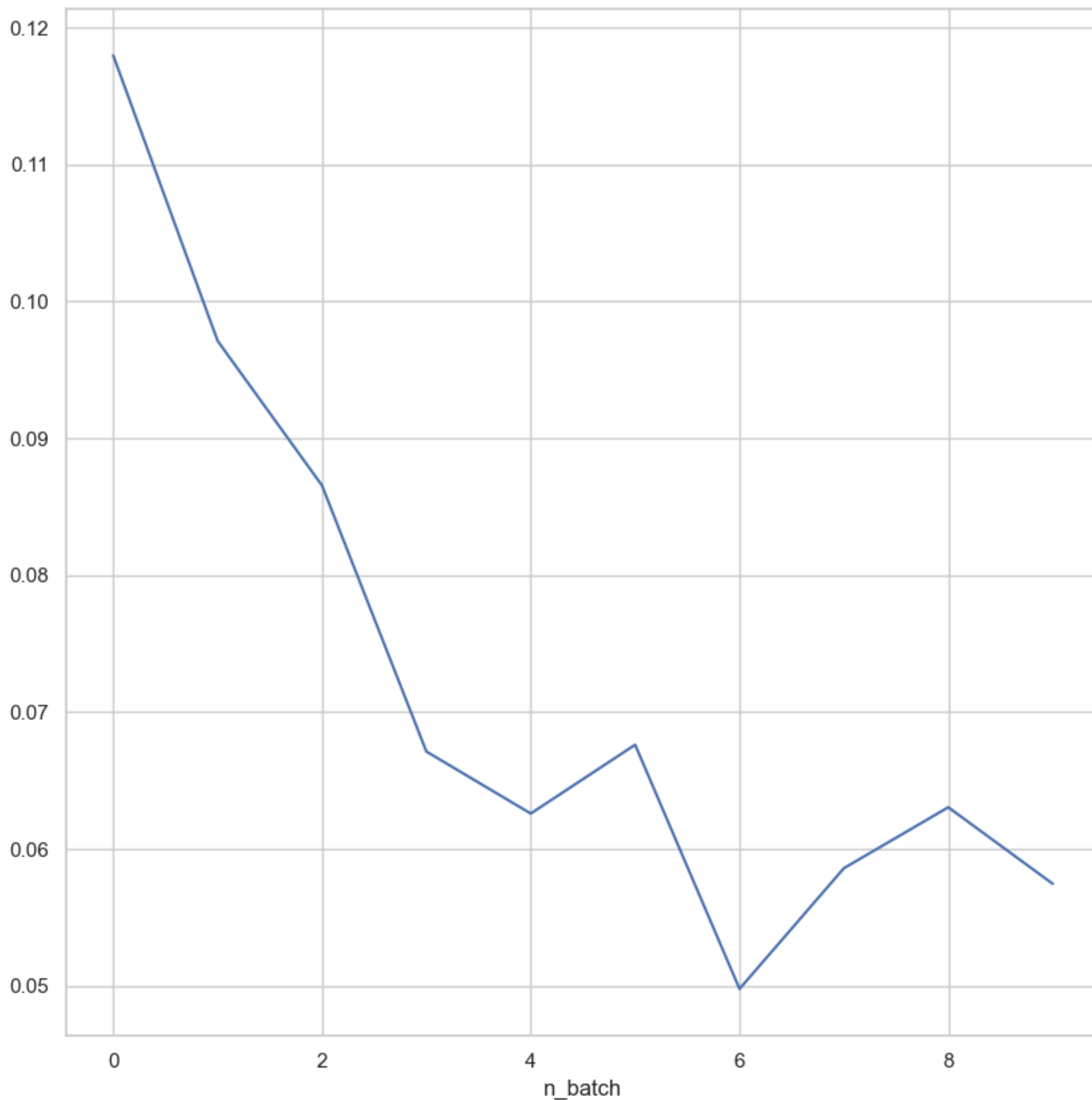



[ ]:

```
# Plot std vs. n

fig, ax = plt.subplots(figsize=(10, 10))

ad_hoc_solutions.groupby("n_batch")["gap"].std().plot(ax=ax)
```

[ ]:

```
<Axes: xlabel='n_batch'>
```



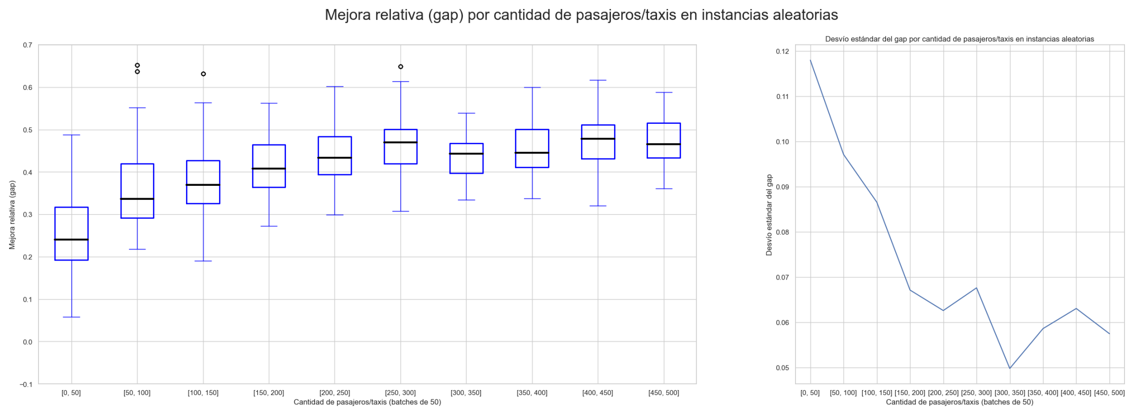

[ ]:
```
ad_hoc_solutions.groupby("n_batch")["gap"].std()
```

[ ]:
```
n_batch
0    0.117963
1    0.097114
2    0.086551
3    0.067112
4    0.062583
5    0.067606
6    0.049773
7    0.058589
8    0.063040
9    0.057453
```

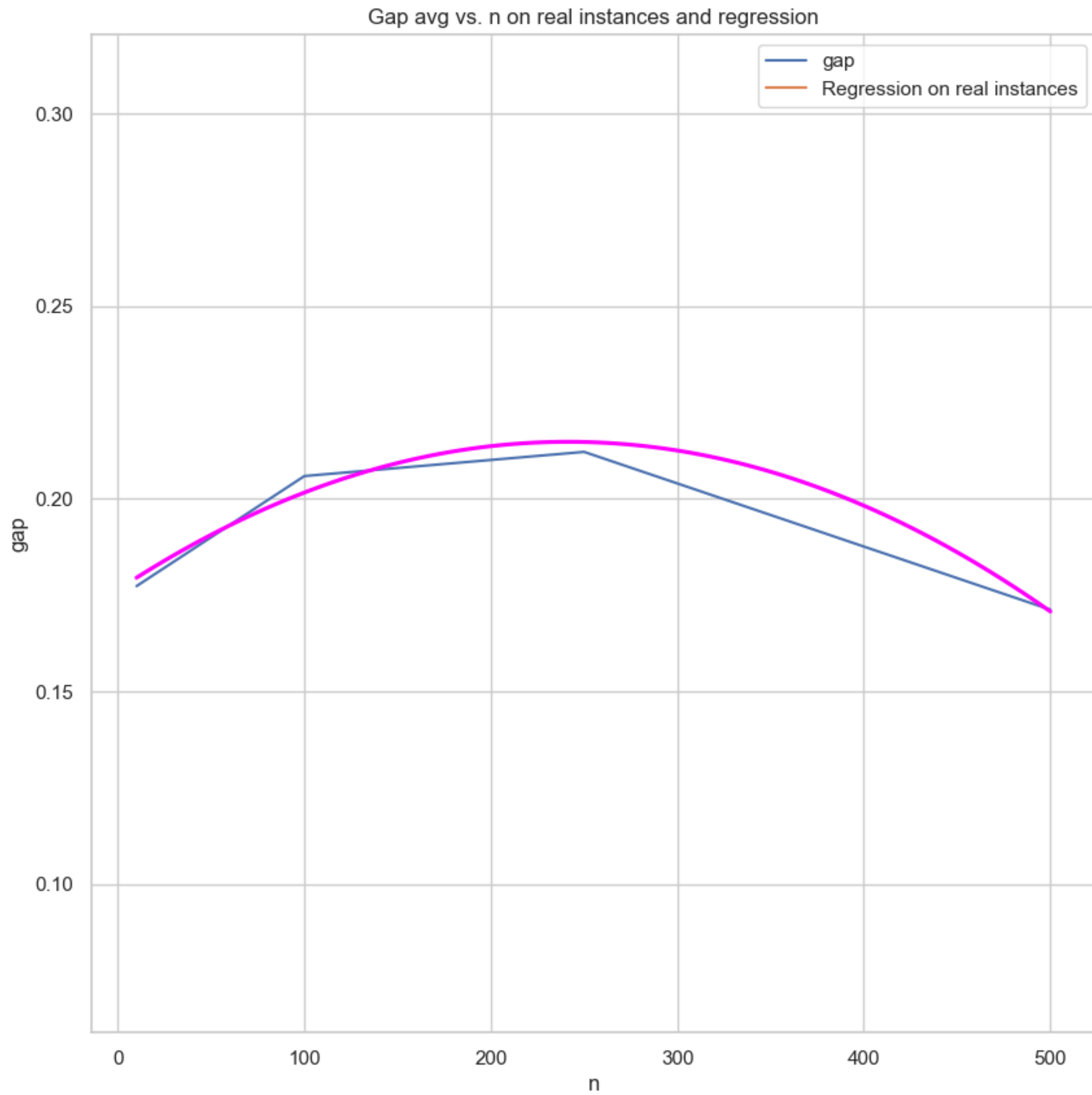
```
Name: gap, dtype: float64
```

[ ]:
```python
fig, axs = plt.subplots(1, 2, figsize=(30, 10), width_ratios=[2, 1])

#boxplot

#ad_hoc_solutions.boxplot(column="gap", by="n", ax=ax)

# Batch ad_hoc_solutions n in batches of 50

ad_hoc_solutions["n_batch"] = ad_hoc_solutions["n"] // 50

ad_hoc_solutions.boxplot(
    column="gap",
    by="n_batch",
    ax=axs[0],
    color="blue",
    boxprops=dict(linestyle='-', linewidth=2, color="blue"),
    medianprops=dict(linestyle='-', linewidth=3, color="black"),
)

#axs[0].set_title("Mejora relativa (gap) por cantidad de pasajeros/taxis en␣
 ↪instancias aleatorias")
axs[0].set_title("")
axs[0].set_xlabel("Cantidad de pasajeros/taxis (batches de 50)")
axs[0].set_ylabel("Mejora relativa (gap)")

# Replace xticks to be the batch number intervals of 50 (0, 50, 100, 150, ...)
# Without affecting the scale of the plot

axs[0].set_xticklabels([f"[{i*50}, {(i+1)*50}]"  for i in range(0, 10)])

axs[0].set_ylim(-0.1, 0.7)

ad_hoc_solutions.groupby("n_batch")["gap"].std().plot(ax=axs[1])

axs[1].set_title("Desvío estándar del gap por cantidad de pasajeros/taxis en␣
 ↪instancias aleatorias")

axs[1].set_xlabel("Cantidad de pasajeros/taxis (batches de 50)")
axs[1].set_ylabel("Desvío estándar del gap")

axs[1].set_xticks(range(0, 10))

axs[1].set_xticklabels([f"[{i*50}, {(i+1)*50}]" for i in range(0, 10)])
```

```
fig.suptitle("Mejora relativa (gap) por cantidad de pasajeros/taxis en instancias aleatorias", fontsize=24)

plt.savefig("../output/figures/gap_vs_n_fake_box_std.png")
```

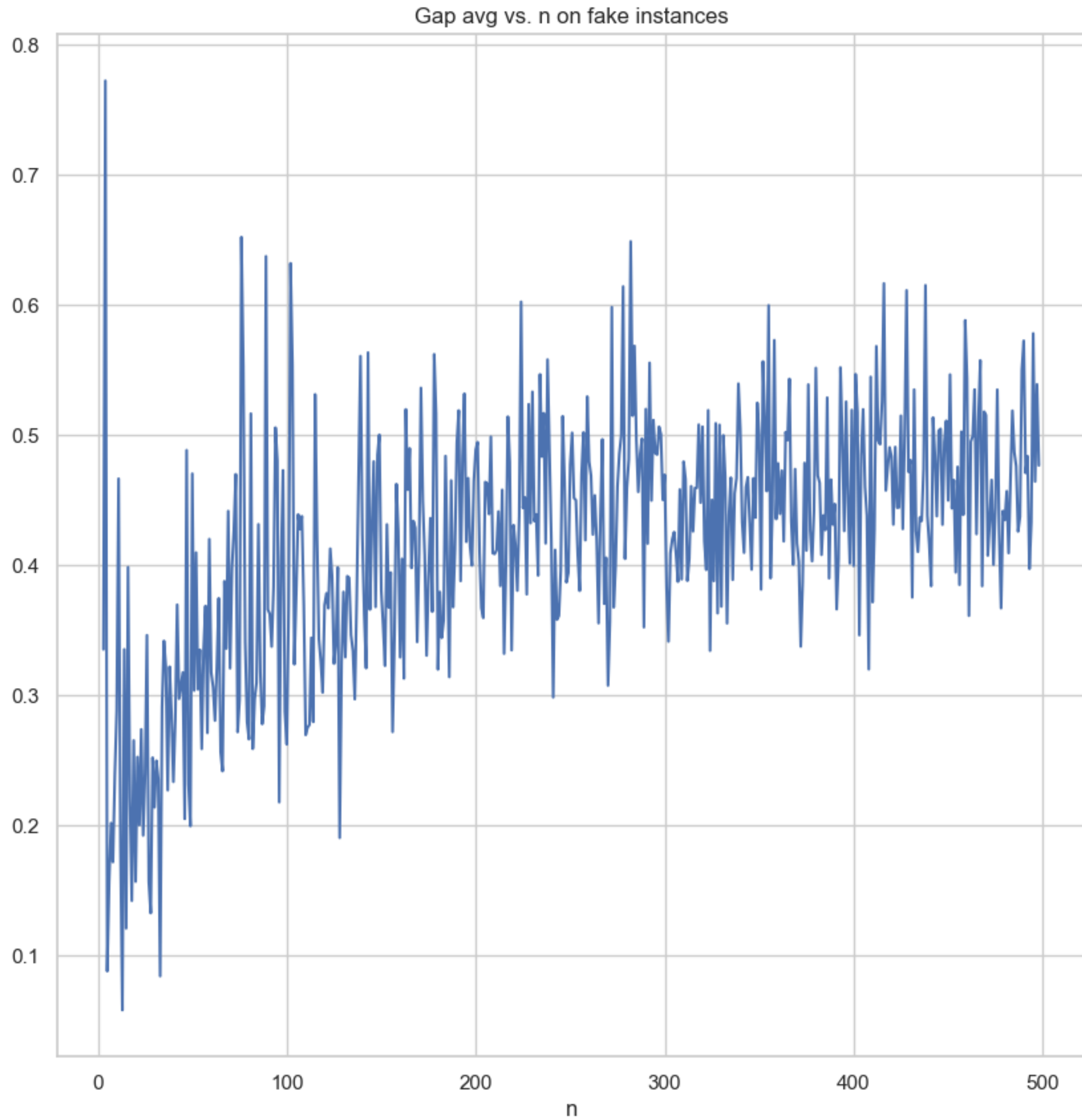



[ ]:
```
fig, ax = plt.subplots(figsize=(10, 10))

solutions.groupby("n")[["gap"]].mean().plot(ax=ax, label="Mean gap")
reg_line = sns.regplot(
                x="n",
                y="gap",
                data=solutions,
                order=2,
                ci=None,
                color="fuchsia",
                marker="",
                ax=ax,
                #label="Regression on real instances",
            )

ax.plot(
    [], [],
    label="Regression on real instances"
)

_ = ax.legend()

ax.set_title("Gap avg vs. n on real instances and regression")

plt.savefig("../output/figures/gap_avg_vs_n_real_reg.png")
```



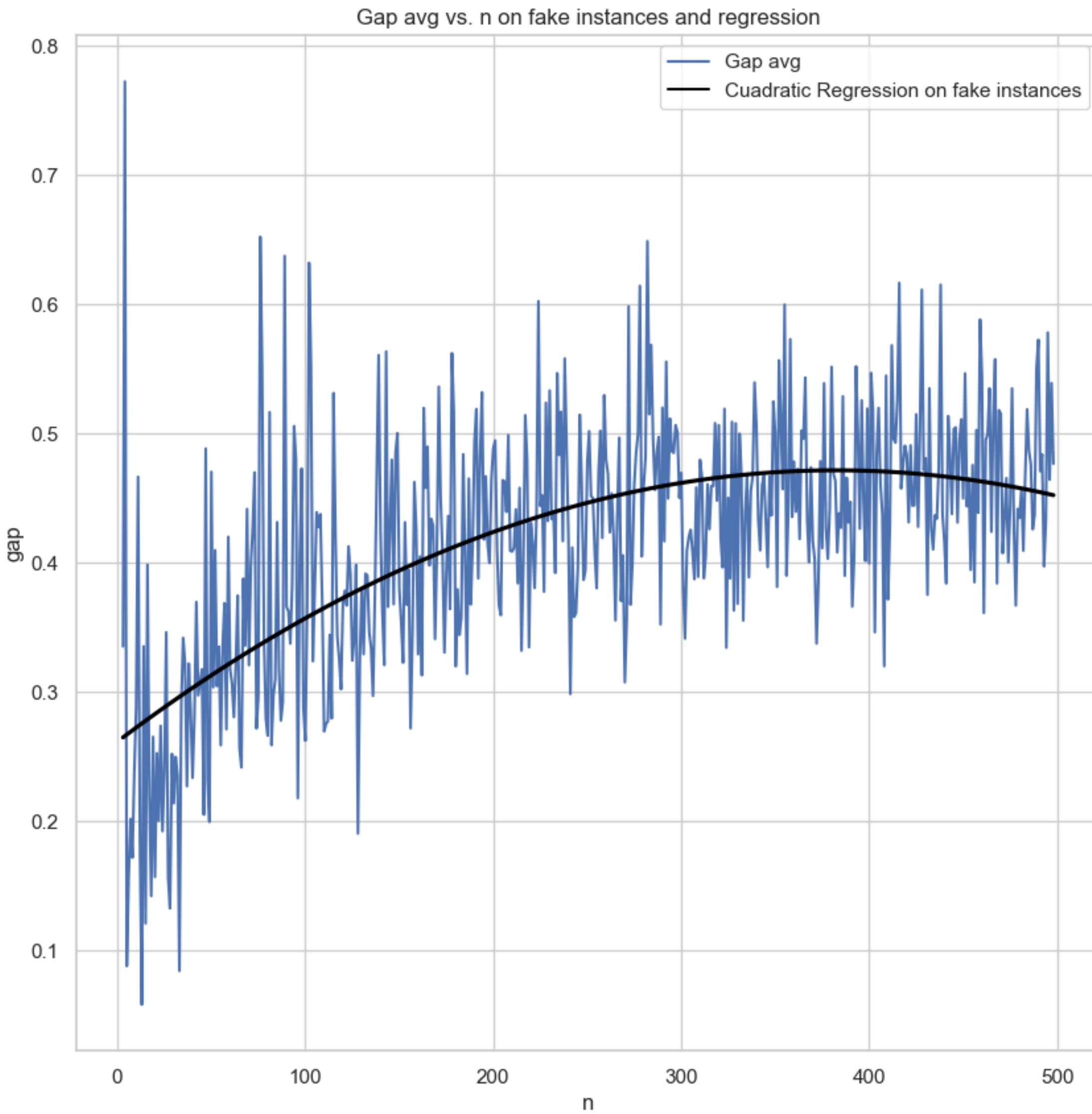

```
[ ]: # Add a regression line

     fig, ax = plt.subplots(figsize=(10, 10))

     #reset axes
     ax = ad_hoc_solutions.groupby("n")["gap"].mean().plot()
     _ = sns.set_theme(style="whitegrid")

     ax.set_title("Gap avg vs. n on fake instances")
     ax.set_xlabel("n")

     ax.plot()
```

[ ]: []




[ ]:
```
# add ns and avg_gaps to the plot
fig, ax = plt.subplots(figsize=(10, 10))

ad_hoc_solutions.groupby("n")["gap"].mean().plot(
    label= "Gap avg",
)

sns.set_theme(style="whitegrid")

ax = sns.regplot(
```

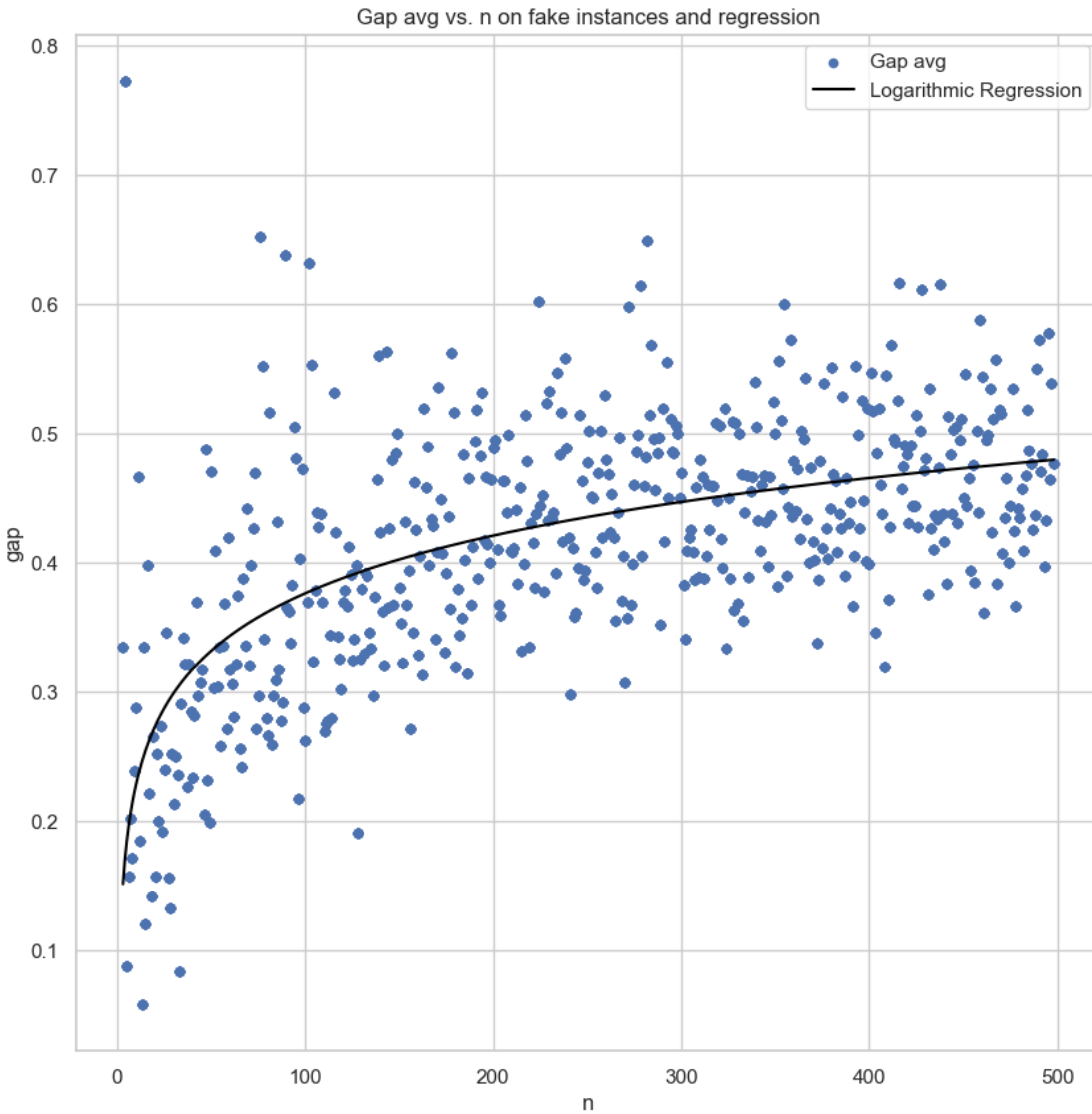
```python
                x="n",
                y="gap",
                data=ad_hoc_solutions,
                order=2,
                ci=None,
                color="black",
                marker="",
            )

ax.plot(
    [], [],
    color="black",
    marker="",
    label="Cuadratic Regression on fake instances",
)

ax.set_title("Gap avg vs. n on fake instances and regression")
ax.set_xlabel("n")

#ax.legend(["Gap avg", "Cuadratic Regression"])
_ = ax.legend()

ax.plot()

plt.savefig("../output/figures/gap_avg_vs_n_fake_reg.png")
```




[ ]:
```
# add ns and avg_gaps to the plot
fig, ax = plt.subplots(figsize=(10, 10))

ad_hoc_solutions.plot.scatter(x="n", y="gap", title="gap vs. n", ax=ax)

sns.set_theme(style="whitegrid")

# Logarithmic regression

log_reg = np.polyfit(
                np.log(ad_hoc_solutions["n"]),
                ad_hoc_solutions["gap"],
```

```
                1
        )
ad_hoc_solutions["reg_log"] = log_reg[0] * np.log(ad_hoc_solutions["n"]) +␣
 ↪log_reg[1]

fake_reg_vals = ad_hoc_solutions.groupby("n")["reg_log"].mean()

ax.plot(fake_reg_vals, color="black", label="Logarithmic regression")

# plot the logarithmic regression line with seaborn

ax.set_title("Gap avg vs. n on fake instances and regression")
ax.set_xlabel("n")

ax.legend(["Gap avg", "Logarithmic Regression"])

ax.plot()

plt.savefig("../output/figures/gap_avg_vs_n_fake_scatter_log_reg.png")
```

```
/Users/nacho/opt/anaconda3/envs/coding/lib/python3.8/site-
packages/pandas/plotting/_matplotlib/core.py:1114: UserWarning: No data for
colormapping provided via 'c'. Parameters 'cmap' will be ignored
  scatter = ax.scatter(
```




```
[ ]: fig, ax = plt.subplots(figsize=(4, 10))

     ax.axis("off")

     mean_res_ = mean_res.drop(columns=["count", "min", "max", "25%", "50%", "75%",␣
      ↪"std"])

     t = ax.table(
         cellText=mean_res_.values,
         colLabels=mean_res_.columns,
         loc="center",
         colWidths=[0.8] * len(mean_res_.columns),
```

```
    cellLoc="center",
    rowLoc="center",
    cellColours= [["#56b5fd" if i % 2 == 0 else "#AAAAFF"] for i in␣
 ↪range(len(mean_res_))],
)

t.auto_set_font_size(False)
t.set_fontsize(16)

# Set the height of each row to 5 units
t.scale(1, 2)
```

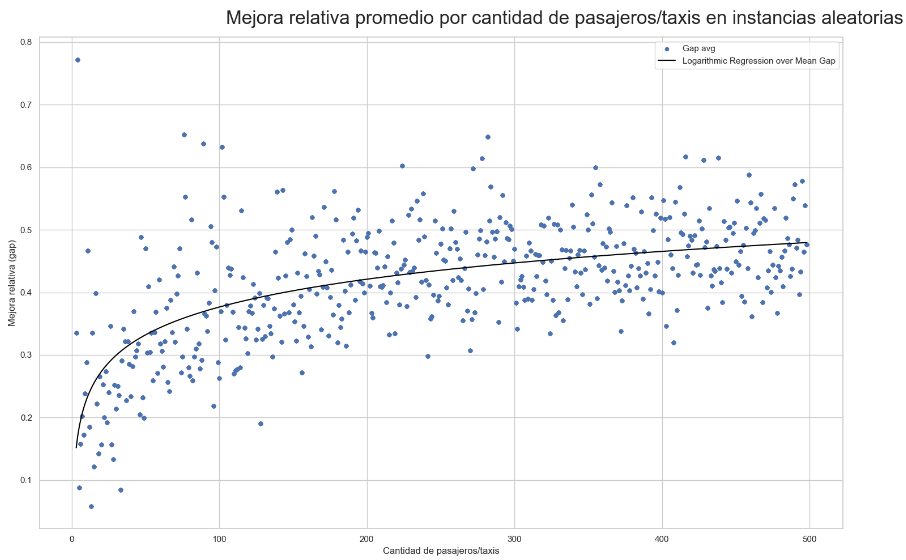
| mean |
| --- |
| 0.335434756750327 |
| 0.4703813286024972 |
| 0.2625078530055437 |
| 0.380709698369173 |
| 0.4887133012651358 |
| 0.47722415771643767 |
| 0.46954617282581584 |
| 0.5004160228218233 |
| 0.3995735304570331 |
| 0.4497883083757007 |
| 0.47667687114878926 |

[ ]:

```python
fig, axs = plt.subplots(1, 2, figsize=(20, 10), width_ratios=[3, 1])

ad_hoc_solutions.plot.scatter(x="n", y="gap", ax=axs[0])
#print(mean_res.drop(columns=["count", "min", "max", "25%", "50%", "75%",␣
↪"std"]).to_markdown())

s = axs[0].plot(fake_reg_vals, color="black", label="Logarithmic regression")

# plot the logarithmic regression line with seaborn

#axs[0].set_title("Mejora relativa (gap) por cantidad de pasajeros/taxis en␣
↪instancias aleatorias")
#axs[0].set_xlabel("n")

axs[0].legend(["Gap avg", "Logarithmic Regression over Mean Gap"])

axs[1].axis("off")

mean_res_ = mean_res.drop(columns=["count", "min", "max", "25%", "50%", "75%",␣
↪"std"])

mean_res_["mean"] = mean_res_["mean"].apply(lambda x: round(x, 4))
mean_res_["n"] = mean_res_.index
# round n to int
mean_res_["n"] = mean_res_["n"].apply(lambda x: "{:.0f}".format(x))
mean_res_["n"] = mean_res_["n"].astype(int)

mean_res_ = mean_res_.reset_index(drop=True)

t = axs[1].table(
    cellText=mean_res_[["n", "mean"]].values,
    colLabels=mean_res_[["n", "mean"]].columns,
    loc="center",
    colWidths=[0.3] * len(mean_res_.columns),
    cellLoc="center",
    rowLoc="center",
    cellColours= [["#ffffff", "#56b5fd" if i % 2 == 0 else "#AAAAFF"] for i in␣
↪range(len(mean_res_))],
)

t.auto_set_font_size(False)
t.set_fontsize(16)

# Set the height of each row to 5 units
t.scale(1, 2)
```

```
# axs[0].title.set_text("Mejora relativa promedio por cantidad de pasajeros/
↪taxis en instancias aleatorias")
axs[0].set_xlabel("Cantidad de pasajeros/taxis")
axs[0].set_ylabel("Mejora relativa (gap)")

fig.suptitle("Mejora relativa promedio por cantidad de pasajeros/taxis en␣
↪instancias aleatorias", fontsize=24)
fig.tight_layout()

plt.savefig("../output/figures/gap_avg_vs_n_fake_scatter_log_reg_table.png")
```

```
/Users/nacho/opt/anaconda3/envs/coding/lib/python3.8/site-
packages/pandas/plotting/_matplotlib/core.py:1114: UserWarning: No data for
colormapping provided via 'c'. Parameters 'cmap' will be ignored
  scatter = ax.scatter(
```




| n | mean |
|---|---|
| 3.0 | 0.3354 |
| 50.0 | 0.4704 |
| 100.0 | 0.2625 |
| 150.0 | 0.3807 |
| 200.0 | 0.4887 |
| 250.0 | 0.4772 |
| 300.0 | 0.4695 |
| 350.0 | 0.5004 |
| 400.0 | 0.3996 |
| 450.0 | 0.4498 |
| 498.0 | 0.4767 |

[ ]:

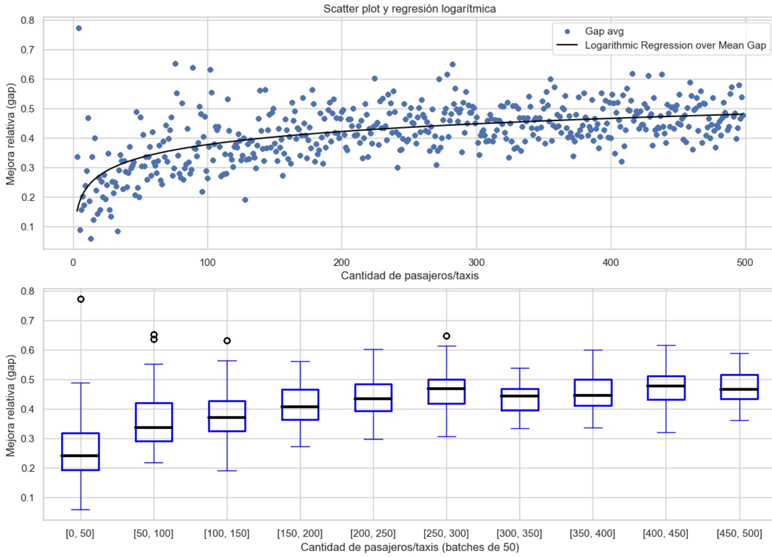
```
fig, axs = plt.subplots(2, 2, figsize=(20, 10), width_ratios=[3, 1],␣
↪height_ratios=[1, 1])

ad_hoc_solutions.plot.scatter(x="n", y="gap", ax=axs[0, 0])
#print(mean_res.drop(columns=["count", "min", "max", "25%", "50%", "75%",␣
↪"std"]).to_markdown())

s = axs[0, 0].plot(fake_reg_vals, color="black", label="Logarithmic regression")

# plot the logarithmic regression line with seaborn
```

```python
#axs[0, 0].set_title("Mejora relativa (gap) por cantidad de pasajeros/taxis en␣
↪instancias aleatorias")
#axs[0, 0].set_xlabel("n")

axs[0, 0].legend(["Gap avg", "Logarithmic Regression over Mean Gap"])

axs[0, 1].axis("off")

mean_res_ = mean_res.drop(columns=["count", "min", "max", "25%", "50%", "75%",␣
↪"std"])

mean_res_["mean"] = mean_res_["mean"].apply(lambda x: round(x, 4))
mean_res_["n"] = mean_res_.index
# round n to int
mean_res_["n"] = mean_res_["n"].apply(lambda x: "{:.0f}".format(x))
mean_res_["n"] = mean_res_["n"].astype(int)

mean_res_ = mean_res_.reset_index(drop=True)

t = axs[0, 1].table(
    cellText=mean_res_[["n", "mean"]].values,
    colLabels=mean_res_[["n", "mean"]].columns,
    loc="center",
    colWidths=[0.3] * len(mean_res_.columns),
    cellLoc="center",
    rowLoc="center",
    cellColours= [["#ffffff", "#56b5fd" if i % 2 == 0 else "#AAAAFF"] for i in␣
↪range(len(mean_res_))],
)

t.auto_set_font_size(False)
t.set_fontsize(16)

# Set the height of each row to 5 units
t.scale(1, 2)

axs[0, 0].title.set_text("Scatter plot y regresión logarítmica")
axs[0, 0].set_xlabel("Cantidad de pasajeros/taxis")
axs[0, 0].set_ylabel("Mejora relativa (gap)")

fig.tight_layout()

#boxplot

#ad_hoc_solutions.boxplot(column="gap", by="n", ax=ax)

# Batch ad_hoc_solutions n in batches of 50
```

```python
ad_hoc_solutions["n_batch"] = ad_hoc_solutions["n"] // 50

ad_hoc_solutions.boxplot(
    column="gap",
    by="n_batch",
    ax=axs[1, 0],
    color="blue",
    boxprops=dict(linestyle='-', linewidth=2, color="blue"),
    medianprops=dict(linestyle='-', linewidth=3, color="black"),
)

axs[1, 1].axis("off")

#ax.set_title("Mejora relativa (gap) por cantidad de pasajeros/taxis en␣
↪instancias aleatorias")
axs[1, 0].set_title("")
axs[1, 0].set_xlabel("Cantidad de pasajeros/taxis (batches de 50)")
axs[1, 0].set_ylabel("Mejora relativa (gap)")

# Replace xticks to be the batch number intervals of 50 (0, 50, 100, 150, ...)
# Without affecting the scale of the plot

axs[1, 0].set_xticklabels([f"[{i*50}, {(i+1)*50}]"  for i in range(0, 10)])

fig.suptitle("Mejora relativa promedio por cantidad de pasajeros/taxis en␣
↪instancias aleatorias", fontsize=24)
#fig.suptitle("Mejora relativa (gap) por cantidad de pasajeros/taxis en␣
↪instancias aleatorias")

plt.savefig("../output/figures/gap_vs_n_fake_box_scatter.png")
```

```
/Users/nacho/opt/anaconda3/envs/coding/lib/python3.8/site-
packages/pandas/plotting/_matplotlib/core.py:1114: UserWarning: No data for
colormapping provided via 'c'. Parameters 'cmap' will be ignored
  scatter = ax.scatter(
```

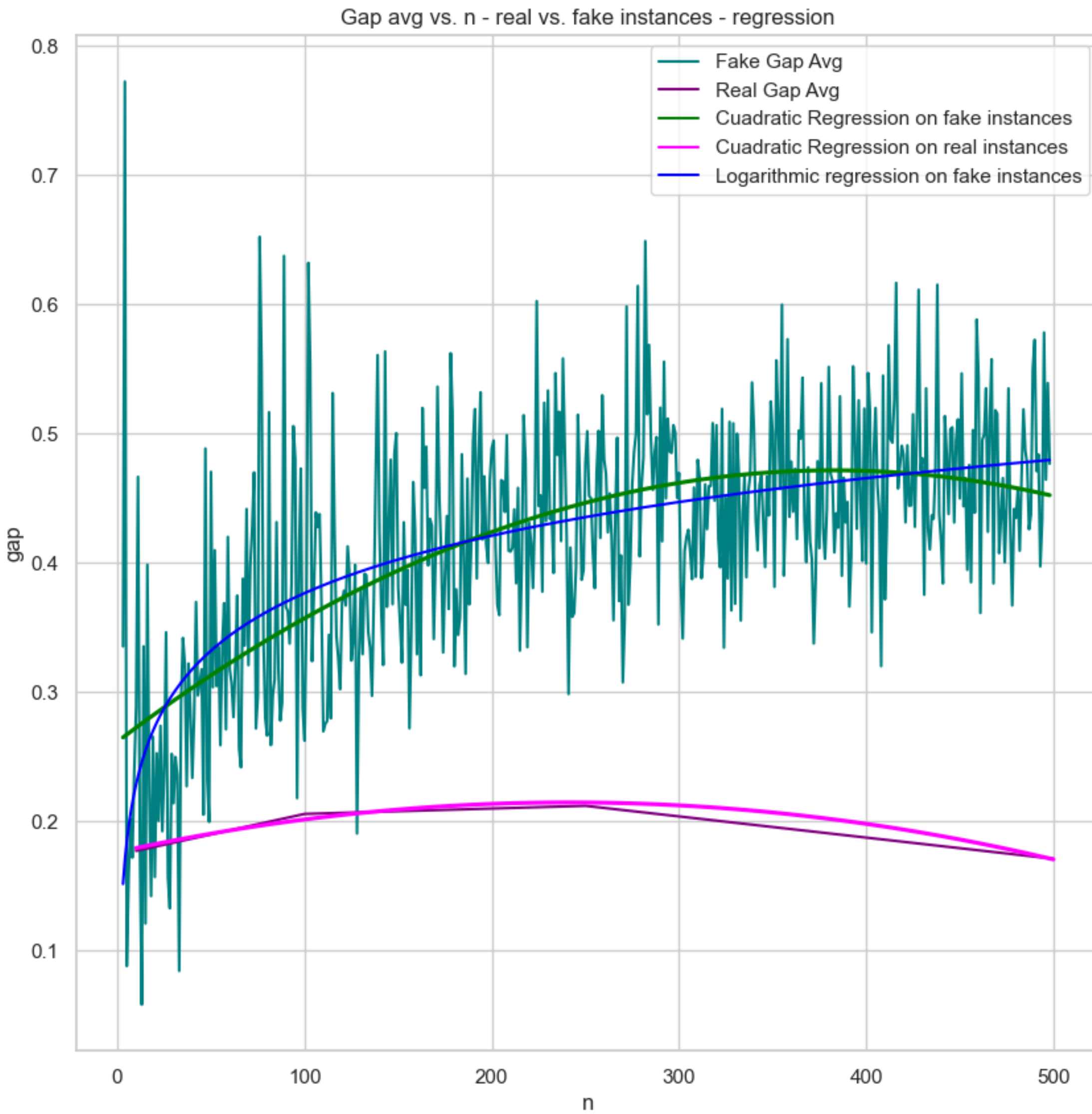
Mejora relativa promedio por cantidad de pasajeros/taxis en instancias aleatorias




| n | mean |
|---|---|
| 3.0 | 0.3354 |
| 50.0 | 0.4704 |
| 100.0 | 0.2625 |
| 150.0 | 0.3807 |
| 200.0 | 0.4887 |
| 250.0 | 0.4772 |
| 300.0 | 0.4695 |
| 350.0 | 0.5004 |
| 400.0 | 0.3996 |
| 450.0 | 0.4498 |
| 498.0 | 0.4767 |

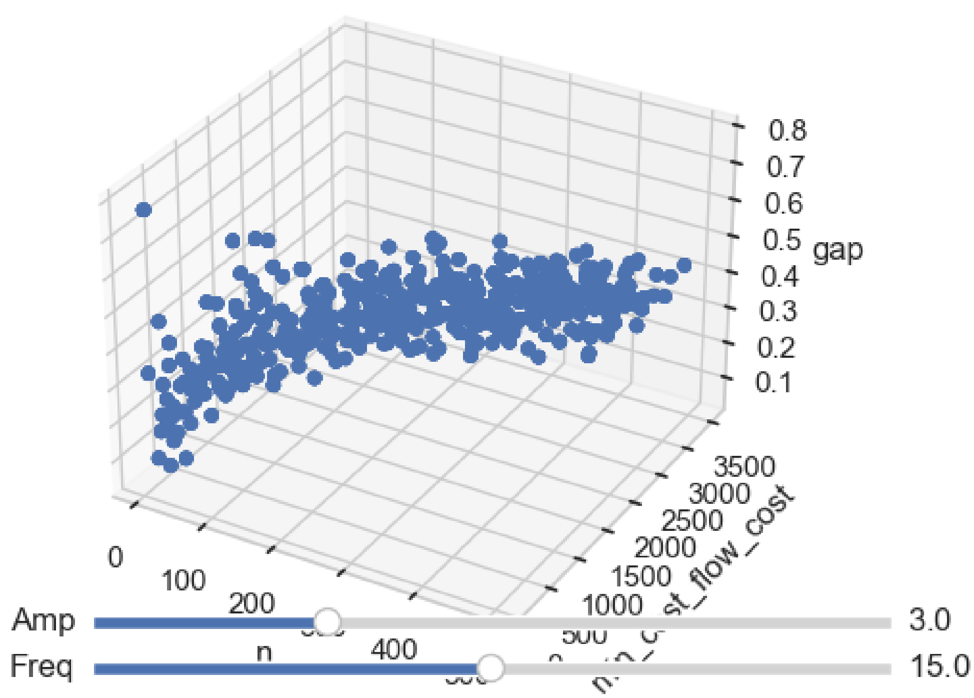
[ ]:
```
fig, ax = plt.subplots(figsize=(10, 10))

fake_vals = ad_hoc_solutions.groupby("n")[["gap"]].mean()
real_vals = solutions.groupby("n")[["gap"]].mean()

ax.plot(fake_vals.index, fake_vals["gap"], color="teal", label="Fake Gap Avg")
ax.plot(real_vals.index, real_vals["gap"], color="purple", label="Real Gap Avg")

# Get regression line for fake instances

reg_line = sns.regplot(
                x="n",
                y="gap",
                data=ad_hoc_solutions,
                order=2,
                ci=None,
                color="green",
                marker="",
                ax=ax,
                #label="Cuadratic Regression on fake instances",
            )

reg_line = sns.regplot(
                x="n",
                y="gap",
                data=solutions,
                order=2,
```

```
                ci=None,
                color="fuchsia",
                marker="",
                ax=ax,
                #label="Cuadratic Regression on real instances",
            )

ax.plot(
    [], [],
    color="green",
    label="Cuadratic Regression on fake instances"
)

ax.plot(
    [], [],
    color="fuchsia",
    label="Cuadratic Regression on real instances"
)

ax.plot(fake_reg_vals, color="blue", label="Logarithmic regression on fake␣
 ↪instances")

ax.set_title("Gap avg vs. n - real vs. fake instances - regression")
ax.set_xlabel("n")

_ = ax.legend()

plt.savefig("../output/figures/gap_avg_vs_n_real_fake_reg.png")
```




```
[ ]: # 3d plot of gap avg vs. n vs. min_cost_flow_cost

import matplotlib.pyplot as plt

fig = plt.figure()

ax = fig.add_subplot(111, projection='3d')

ax.scatter(ad_hoc_solutions["n"], ad_hoc_solutions["min_cost_flow_cost"],␣
 ↪ad_hoc_solutions["gap"])

ax.set_xlabel('n')
```

```
ax.set_ylabel('min_cost_flow_cost')

ax.set_zlabel('gap')

# Make the plot rotate interactively

from matplotlib.widgets import Slider, Button, RadioButtons

axcolor = 'lightgoldenrodyellow'

axfreq = plt.axes([0.25, 0.1, 0.65, 0.03], facecolor=axcolor)

axamp = plt.axes([0.25, 0.15, 0.65, 0.03], facecolor=axcolor)

sfreq = Slider(axfreq, 'Freq', 0.1, 30.0, valinit=15)

samp = Slider(axamp, 'Amp', 0.1, 10.0, valinit=3)

# Open the interactive plot in a new window outside of Jupyter

plt.show()
```

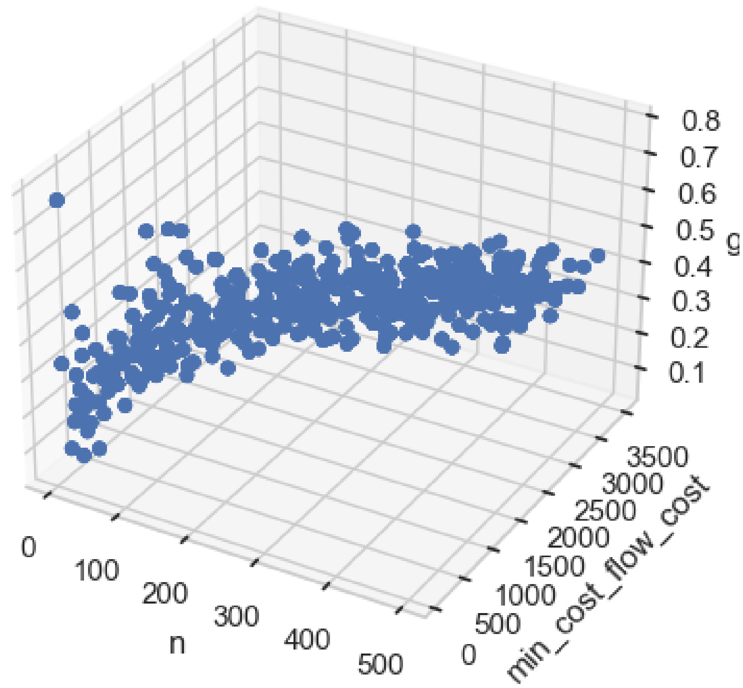


[ ]:

```python
# Add a regression plane

import numpy as np

np.float = np.float64

from sklearn.linear_model import LinearRegression

from sklearn.preprocessing import PolynomialFeatures

from sklearn.pipeline import make_pipeline

#reset axes

fig = plt.figure()

ax = fig.add_subplot(111, projection='3d')

ax.scatter(ad_hoc_solutions["n"], ad_hoc_solutions["min_cost_flow_cost"],␣
↪ad_hoc_solutions["gap"])

ax.set_xlabel('n')

ax.set_ylabel('min_cost_flow_cost')

ax.set_zlabel('gap')

# model.fit(X, y)

# Input contains NaN, infinity or a value too large for dtype('float64').

# To fix this, we can cap the max value of X
```

[ ]:

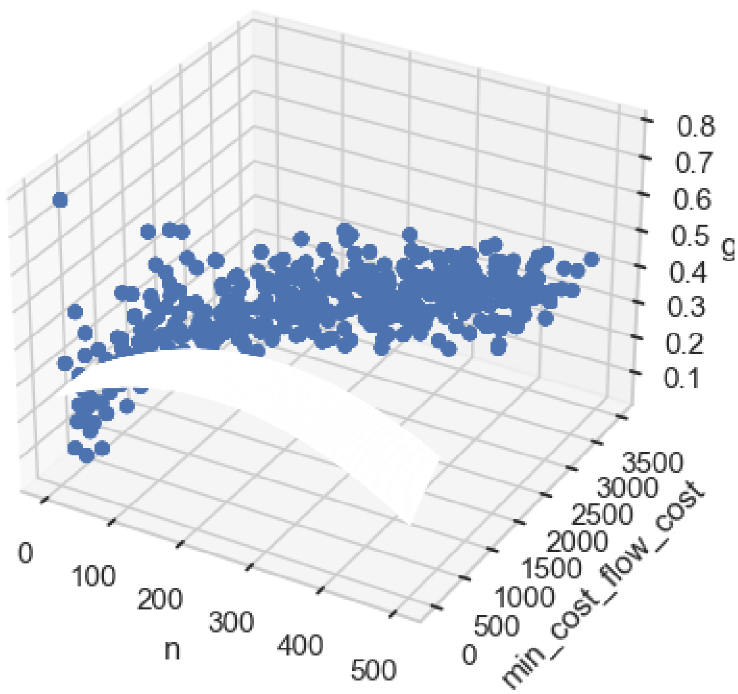
```
Text(0.5, 0, 'gap')
```




[ ]:
```
fig = plt.figure()

ax = fig.add_subplot(111, projection='3d')

ax.scatter(ad_hoc_solutions["n"], ad_hoc_solutions["min_cost_flow_cost"],␣
 ↪ad_hoc_solutions["gap"])

ax.set_xlabel('n')

ax.set_ylabel('min_cost_flow_cost')

ax.set_zlabel('gap')

# Add a regression plane

X = ad_hoc_solutions[["n", "min_cost_flow_cost"]]
y = ad_hoc_solutions["gap"]

model = make_pipeline(PolynomialFeatures(2), LinearRegression())

model.fit(X, y)
```

```
xx, yy = np.meshgrid(np.linspace(0, 500, 100), np.linspace(0, 500, 100))

zz = np.array([xx.flatten(), yy.flatten()]).T

zz = model.predict(zz)

zz = zz.reshape(xx.shape)

ax.plot_surface(xx, yy, zz, color="blue", alpha=0.5)
```

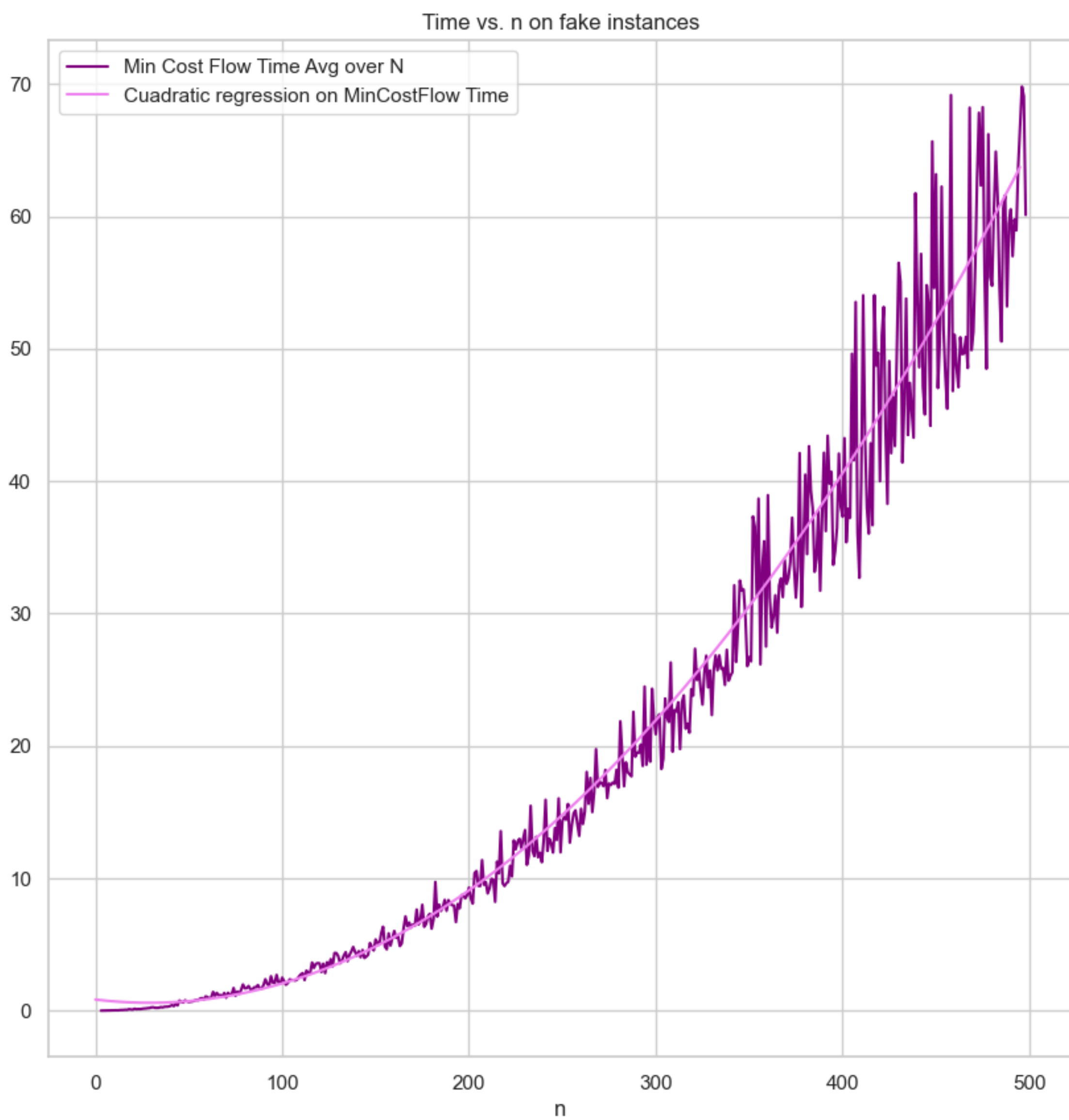
[ ]: <mpl_toolkits.mplot3d.art3d.Poly3DCollection at 0x7f8a0e8115b0>




### 0.2.1 Comparación de tiempos de ejecución

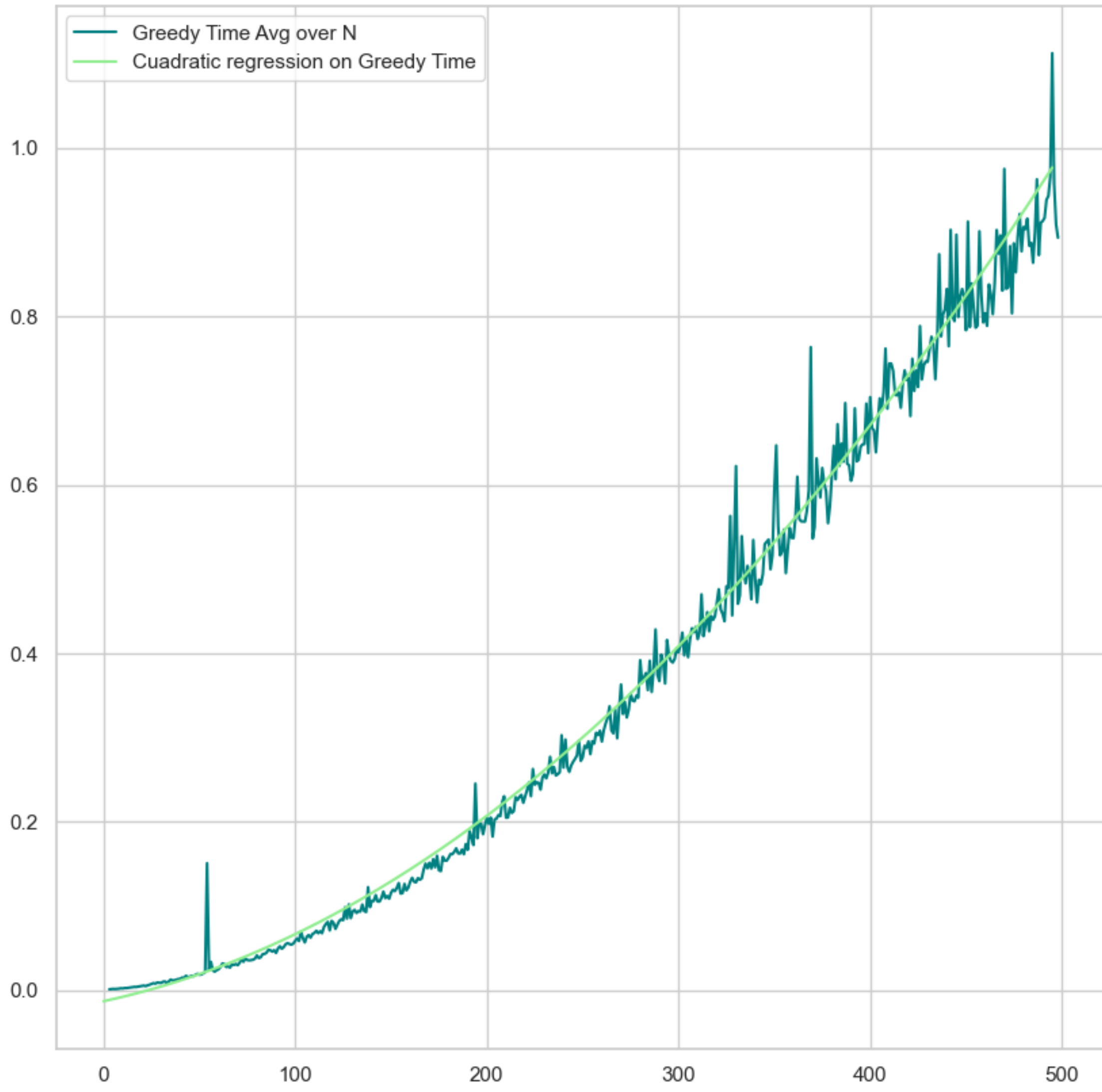
[ ]:
```
# Analisis de tiempo de ejecucion

ad_hoc_solutions["greedy_time"] = ad_hoc_solutions["greedy_time"].apply(lambda␣
↪x: float(x))
ad_hoc_solutions["min_cost_flow_time"] = ad_hoc_solutions["min_cost_flow_time"].
↪apply(lambda x: float(x))

# Plot time vs. n
```

```
fig, ax = plt.subplots(figsize=(10, 10))

greedy_times = ad_hoc_solutions.groupby("n")[["greedy_time"]].mean()
min_cost_flow_times = ad_hoc_solutions.groupby("n")[["min_cost_flow_time"]].
 ↪mean()

"""
ax.plot(greedy_times,
        color="teal",
        label="Greedy Time Avg over N")
 """

ax.plot(min_cost_flow_times,
        color="purple",
        label="Min Cost Flow Time Avg over N")


# Cuadratic regression of min_cost_flow_time

exp_reg = np.poly1d(np.polyfit(min_cost_flow_times.index,␣
 ↪min_cost_flow_times["min_cost_flow_time"], 2))

exp_reg_vals = exp_reg(min_cost_flow_times.index)

ax.plot(exp_reg_vals,
        color="Violet",
        label="Cuadratic regression on MinCostFlow Time")

ax.set_title("Time vs. n on fake instances")
ax.set_xlabel("n")

_ = ax.legend()

plt.savefig("../output/figures/time_vs_n_mincostflow_fake_scatter.png")

# Plot time vs. n
```




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

_ = ax.plot(greedy_times,
        color="teal",
        label="Greedy Time Avg over N")

# Cuadratic regression of greedy_time

reg = np.poly1d(np.polyfit(greedy_times.index, greedy_times["greedy_time"], 2))

reg_vals = reg(greedy_times.index)
```

```
ax.plot(reg_vals,
        color="lightgreen",
        label="Cuadratic regression on Greedy Time")

_ = ax.legend(loc="upper left")

plt.savefig("../output/figures/time_vs_n_greedy_fake_scatter.png")
```

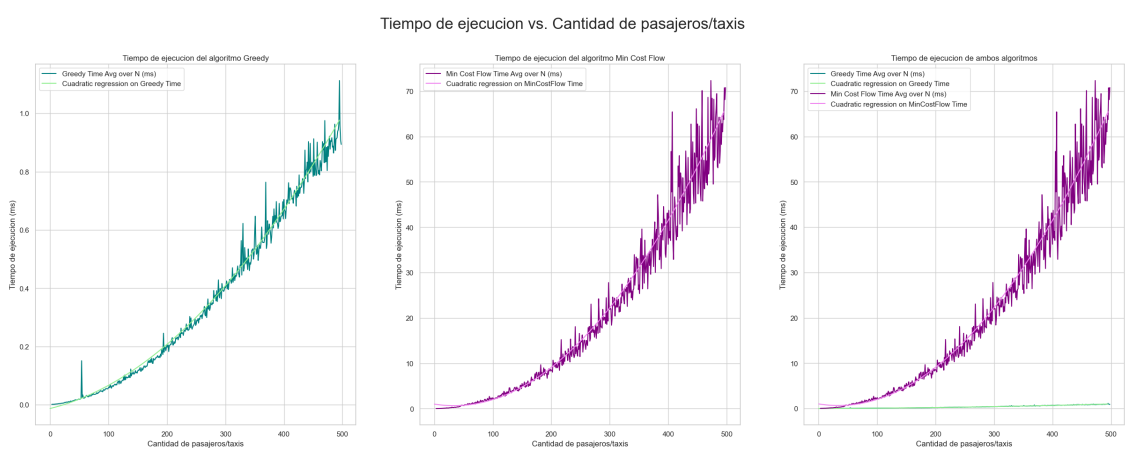



[ ]:
```
fit, axs = plt.subplots(1, 3, figsize=(30, 10))

axs[0].plot(greedy_times,
        color="teal",
```

```
        label="Greedy Time Avg over N (ms)")

axs[0].plot(reg_vals,
        color="lightgreen",
        label="Cuadratic regression on Greedy Time")

axs[0].legend(loc="upper left")

axs[0].set_xlabel("Cantidad de pasajeros/taxis")
axs[0].set_ylabel("Tiempo de ejecucion (ms)")

axs[0].set_title("Tiempo de ejecucion del algoritmo Greedy")

axs[1].plot(min_cost_flow_times,
        color="purple",
        label="Min Cost Flow Time Avg over N (ms)")

axs[1].plot(exp_reg_vals,
        color="Violet",
        label="Cuadratic regression on MinCostFlow Time")

axs[1].legend()

axs[1].set_xlabel("Cantidad de pasajeros/taxis")
axs[1].set_ylabel("Tiempo de ejecucion (ms)")

axs[1].set_title("Tiempo de ejecucion del algoritmo Min Cost Flow")

axs[2].plot(greedy_times,
        color="teal",
        label="Greedy Time Avg over N (ms)")

axs[2].plot(reg_vals,
        color="lightgreen",
        label="Cuadratic regression on Greedy Time")

axs[2].plot(min_cost_flow_times,
        color="purple",
        label="Min Cost Flow Time Avg over N (ms)")

axs[2].plot(exp_reg_vals,
        color="Violet",
        label="Cuadratic regression on MinCostFlow Time")

axs[2].legend()

axs[2].set_xlabel("Cantidad de pasajeros/taxis")
```

```python
axs[2].set_ylabel("Tiempo de ejecucion (ms)")

axs[2].set_title("Tiempo de ejecucion de ambos algoritmos")

plt.suptitle("Tiempo de ejecucion vs. Cantidad de pasajeros/taxis", fontsize=24)

# print min max values of greedy and min_cost_flow

print("Greedy min time: ", ad_hoc_solutions["greedy_time"].min())
print("Greedy max time: ", ad_hoc_solutions["greedy_time"].max())

print("Min Cost Flow min time: ", ad_hoc_solutions["min_cost_flow_time"].min())
print("Min Cost Flow max time: ", ad_hoc_solutions["min_cost_flow_time"].max())

# Print mean min max values of greedy and min_cost_flow

print("Greedy mean time: ", ad_hoc_solutions["greedy_time"].mean())
print("Greedy std time: ", ad_hoc_solutions["greedy_time"].std())

print("Min Cost Flow mean time: ", ad_hoc_solutions["min_cost_flow_time"].
 ↪mean())
print("Min Cost Flow std time: ", ad_hoc_solutions["min_cost_flow_time"].std())

plt.savefig("../output/figures/greedy_vs_batching_time.png")
```

```
Greedy min time:  0.000959
Greedy max time:  1.94525
Min Cost Flow min time:  0.018
Min Cost Flow max time:  179.911
Greedy mean time:  0.3556519286290322
Greedy std time:  0.29416791397762554
Min Cost Flow mean time:  20.817871655645163
Min Cost Flow std time:  20.07008868264632
```



## 0.3 Taxi Priority

[ ]:
```
taxi_priorities_og = pd.read_csv("../output/taxi_priorities_original.csv")
taxi_priorities_og.describe()
```

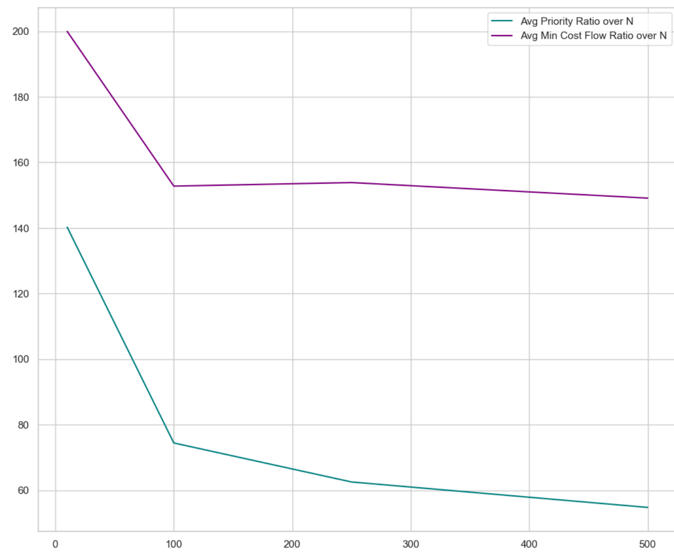
[ ]:
```
                n  avg_priority_ratio  avg_min_cost_flow_ratio  \
count   40.000000           40.000000                40.000000
mean   215.000000           82.983092               163.930615
std    187.903412           47.295148                50.666982
min     10.000000           44.190100                86.093600
25%     77.500000           58.235675               139.775500
50%    175.000000           67.875000               150.465500
75%    312.500000           85.760425               178.405500
max    500.000000          264.085000               373.980000

       avg_greedy_ratio
count         40.000000
mean         199.389650
std           70.477647
min          108.345000
25%          156.981250
50%          176.264500
75%          212.591250
max          433.235000
```

[ ]:
```
# plot taxi priorities avg_priority_ratio vs avg_min_cost_flow_ratio
# group by n

taxi_priorities_og["avg_priority_ratio"] =␣
 ↪taxi_priorities_og["avg_priority_ratio"].apply(lambda x: float(x))
taxi_priorities_og["avg_min_cost_flow_ratio"] =␣
 ↪taxi_priorities_og["avg_min_cost_flow_ratio"].apply(lambda x: float(x))

fig, axs = plt.subplots(1, 2, figsize=(20, 10), width_ratios=[2, 1])

_ = axs[0].plot(taxi_priorities_og.groupby("n")[["avg_priority_ratio"]].mean(),
        color="teal",
        label="Avg Priority Ratio over N")

_ = axs[0].plot(taxi_priorities_og.groupby("n")[["avg_min_cost_flow_ratio"]].
 ↪mean(),
        color="purple",
        label="Avg Min Cost Flow Ratio over N")

_ = axs[0].legend()
```

```
# Table with avg_priority_ratio and avg_min_cost_flow_ratio grouped by n

mean_taxi_pri = taxi_priorities_og.groupby("n")[["avg_priority_ratio",␣
↪"avg_min_cost_flow_ratio"]].mean().round(2)


t = axs[1].table(
        cellText=mean_taxi_pri.values,
        rowLabels=mean_taxi_pri.index,
        colLabels=mean_taxi_pri.columns,
        loc="center",
        colWidths=[0.6] * len(mean_taxi_pri.columns),
        cellLoc="center",
        rowLoc="center",
        #cellColours= [["#56b5fd" if i % 2 == 0 else "#AAAAFF"] for i in␣
↪range(len(mean_taxi_pri.columns))],
)

t.auto_set_font_size(False)
t.set_fontsize(16)
t.scale(1, 2)
_ = axs[1].axis("off")

fig.suptitle("Comparacion de Costo de Taxistas vs. Cantidad de pasajeros/taxis␣
↪en Instancias Originales", fontsize=24)

#plt.savefig("../output/figures/taxi_priorities_original.png")
```

[ ]:
```
Text(0.5, 0.98, 'Comparacion de Costo de Taxistas vs. Cantidad de
pasajeros/taxis en Instancias Originales')
```

Comparacion de Costo de Taxistas vs. Cantidad de pasajeros/taxis en Instancias Originales



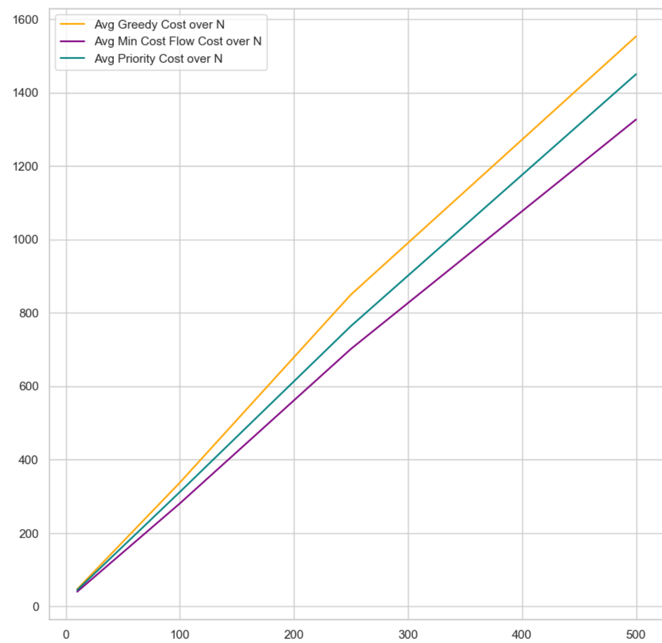

| | avg_priority_ratio | avg_min_cost_flow_ratio |
|---|---|---|
| 10 | 140.25 | 199.97 |
| 100 | 74.41 | 152.77 |
| 250 | 62.52 | 153.86 |
| 500 | 54.75 | 149.11 |

[ ]:

```
# plot from solutions, greedy_cost vs min_cost_flow_cost vs priority_cost

solutions["greedy_cost"] = solutions["greedy_cost"].apply(lambda x: float(x))
solutions["min_cost_flow_cost"] = solutions["min_cost_flow_cost"].apply(lambda x: float(x))
solutions["priority_cost"] = solutions["priority_cost"].apply(lambda x: float(x))

fig, ax = plt.subplots(figsize=(10, 10))

_ = ax.plot(solutions.groupby("n")[["greedy_cost"]].mean(),
        color="orange",
        label="Avg Greedy Cost over N")

_ = ax.plot(solutions.groupby("n")[["min_cost_flow_cost"]].mean(),
        color="purple",
        label="Avg Min Cost Flow Cost over N")

_ = ax.plot(solutions.groupby("n")[["priority_cost"]].mean(),
        color="teal",
        label="Avg Priority Cost over N")

_ = ax.legend()

fig.suptitle("Comparacion de Costo de Soluciones vs. Cantidad de pasajeros/taxis en Instancias Originales", fontsize=24)
```

```
plt.savefig("../output/figures/solutions_original.png")
```

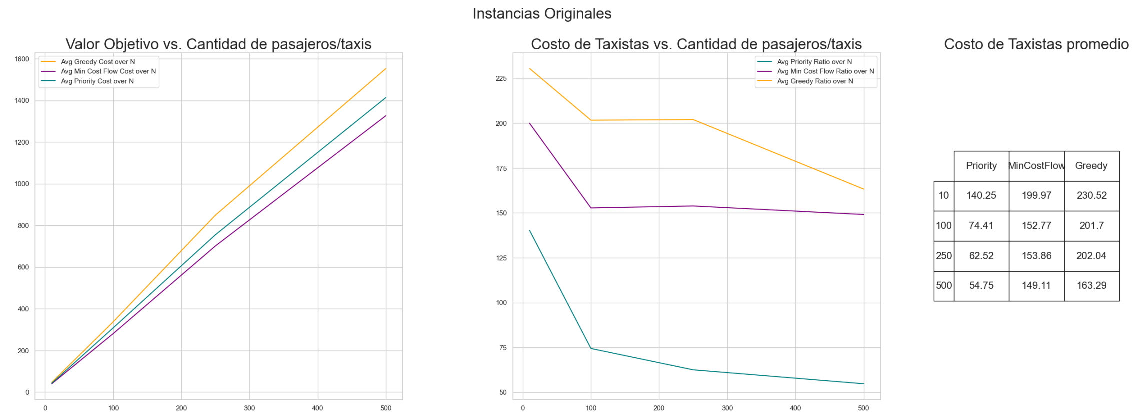
Comparacion de Costo de Soluciones vs. Cantidad de pasajeros/taxis en Instancias Originales




[ ]:
```
fig, axs = plt.subplots(1, 3, figsize=(30, 10), width_ratios=[4, 4, 1])

_ = axs[0].plot(solutions.groupby("n")[["greedy_cost"]].mean(),
        color="orange",
        label="Avg Greedy Cost over N")

_ = axs[0].plot(solutions.groupby("n")[["min_cost_flow_cost"]].mean(),
        color="purple",
        label="Avg Min Cost Flow Cost over N")

_ = axs[0].plot(solutions.groupby("n")[["priority_cost"]].mean(),
        color="teal",
        label="Avg Priority Cost over N")

_ = axs[0].legend()

_ = axs[1].plot(taxi_priorities_og.groupby("n")[["avg_priority_ratio"]].mean(),
        color="teal",
        label="Avg Priority Ratio over N")
```

```
_ = axs[1].plot(taxi_priorities_og.groupby("n")[["avg_min_cost_flow_ratio"]].
 ↪mean(),
        color="purple",
        label="Avg Min Cost Flow Ratio over N")

_ = axs[1].plot(taxi_priorities_og.groupby("n")[["avg_greedy_ratio"]].mean(),
        color="orange",
        label="Avg Greedy Ratio over N")

_ = axs[1].legend()

# Table with avg_priority_ratio and avg_min_cost_flow_ratio grouped by n

mean_taxi_pri = taxi_priorities_og.groupby("n")[["avg_priority_ratio",␣
 ↪"avg_min_cost_flow_ratio", "avg_greedy_ratio"]].mean().round(2)

mean_taxi_pri.columns = ["Priority", "MinCostFlow", "Greedy"]

t = axs[2].table(
        cellText=mean_taxi_pri.values,
        rowLabels=mean_taxi_pri.index,
        colLabels=mean_taxi_pri.columns,
        loc="center",
        colWidths=[0.6] * len(mean_taxi_pri.columns),
        cellLoc="center",
        rowLoc="center",
        #cellColours= [["#56b5fd" if i % 2 == 0 else "#AAAAFF"] for i in␣
 ↪range(len(mean_taxi_pri.columns))],
)

t.auto_set_font_size(False)
t.set_fontsize(16)
t.scale(1, 4)
_ = axs[2].axis("off")


axs[0].set_title("Valor Objetivo vs. Cantidad de pasajeros/taxis", fontsize=24)
axs[1].set_title("Costo de Taxistas vs. Cantidad de pasajeros/taxis",␣
 ↪fontsize=24)
axs[2].set_title("Costo de Taxistas promedio", fontsize=24)

# set space between plots

fig.subplots_adjust(wspace=0.4)

fig.suptitle("Instancias Originales", fontsize=24)
```

```
plt.savefig("../output/figures/results_combined_original.png")
```



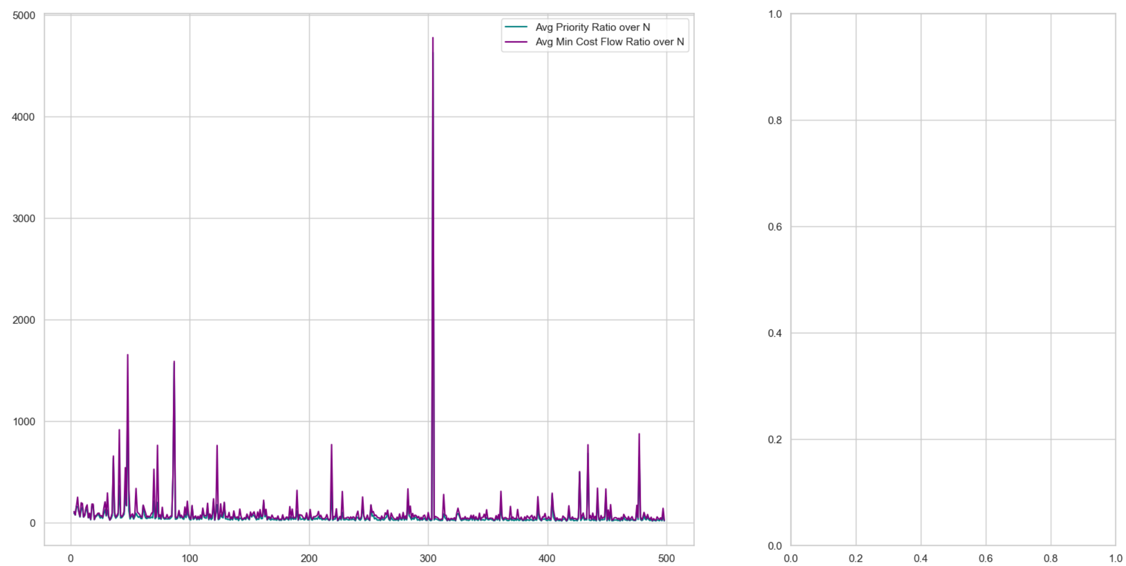

| | Priority | MinCostFlow | Greedy |
|---|---|---|---|
| 10 | 140.25 | 199.97 | 230.52 |
| 100 | 74.41 | 152.77 | 201.7 |
| 250 | 62.52 | 153.86 | 202.04 |
| 500 | 54.75 | 149.11 | 163.29 |

[ ]:
```
taxi_priorities_rand = pd.read_csv("../output/fake/taxi_priorities_random.csv")

taxi_priorities_rand["avg_priority_ratio"] =␣
 ↪taxi_priorities_rand["avg_priority_ratio"].apply(lambda x: float(x))
taxi_priorities_rand["avg_min_cost_flow_ratio"] =␣
 ↪taxi_priorities_rand["avg_min_cost_flow_ratio"].apply(lambda x: float(x))
taxi_priorities_rand["avg_greedy_ratio"] =␣
 ↪taxi_priorities_rand["avg_greedy_ratio"].apply(lambda x: float(x))

taxi_priorities_rand.describe()
```

[ ]:
```
                 n  avg_priority_ratio  avg_min_cost_flow_ratio  \
count  4960.000000         4960.000000              4960.000000
mean    250.500000           67.395563                98.696155
std     143.197012          232.789721               255.776086
min       3.000000           13.916200                18.571100
25%     126.750000           24.974900                37.601125
50%     250.500000           32.462850                52.413400
75%     374.250000           52.104275                79.003725
max     498.000000         4630.790000              4777.720000

       avg_greedy_ratio
count       4960.000000
mean         137.109841
std          338.082502
min           24.875100
25%           51.104400
50%           68.219650
75%          110.616750
max         4729.550000
```

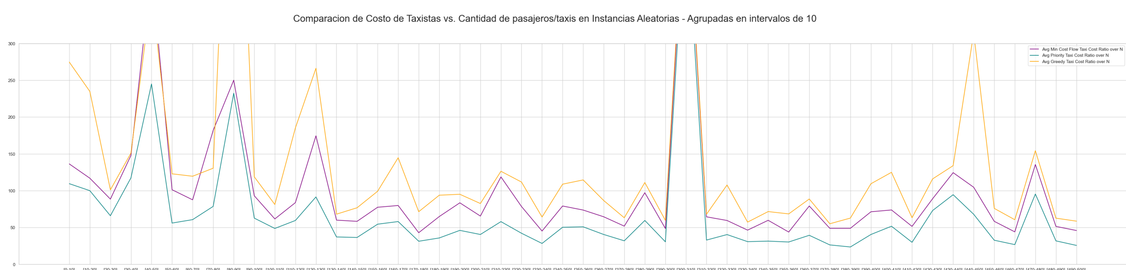
```
[ ]: fig, axs = plt.subplots(1, 2, figsize=(20, 10), width_ratios=[2, 1])

_ = axs[0].plot(taxi_priorities_rand.groupby("n")[["avg_priority_ratio"]].
 ↪mean(),
        color="teal",
        label="Avg Priority Ratio over N")

_ = axs[0].plot(taxi_priorities_rand.groupby("n")[["avg_min_cost_flow_ratio"]].
 ↪mean(),
        color="purple",
        label="Avg Min Cost Flow Ratio over N")

_ = axs[0].legend()

# Table with avg_priority_ratio and avg_min_cost_flow_ratio grouped by n

mean_taxi_pri_rand = taxi_priorities_rand.groupby("n")[["avg_priority_ratio",␣
 ↪"avg_min_cost_flow_ratio"]].mean().round(2)

""" t = axs[1].table(
        cellText=mean_taxi_pri_rand.values,
        rowLabels=mean_taxi_pri_rand.index,
        colLabels=mean_taxi_pri_rand.columns,
        loc="center",
        colWidths=[0.6] * len(mean_taxi_pri_rand.columns),
        cellLoc="center",
        rowLoc="center",
        #cellColours= [["#56b5fd" if i % 2 == 0 else "#AAAAFF"] for i in␣
 ↪range(len(mean_taxi_pri.columns))],
)

t.auto_set_font_size(False)
t.set_fontsize(16)
t.scale(1, 2) """

fig.suptitle("Comparacion de Costo de Taxistas vs. Cantidad de pasajeros/taxis␣
 ↪en Instancias Aleatorias", fontsize=24)

plt.savefig("../output/figures/taxi_priorities_random.png")
```

Comparacion de Costo de Taxistas vs. Cantidad de pasajeros/taxis en Instancias Aleatorias




```
[ ]: # Bar plot with avg_priority_ratio and avg_min_cost_flow_ratio grouped by n

fig, ax = plt.subplots(figsize=(50, 10))

# Group in batches of 50

taxi_priorities_rand["batch"] = taxi_priorities_rand["n"].apply(lambda x: x //
 ↪10)


_ = ax.plot(taxi_priorities_rand.groupby("batch")[["avg_min_cost_flow_ratio"]].
 ↪mean(),
        color="purple",
        label="Avg Min Cost Flow Taxi Cost Ratio over N")

_ = ax.plot(taxi_priorities_rand.groupby("batch")[["avg_priority_ratio"]].
 ↪mean(),
        color="teal",
        label="Avg Priority Taxi Cost Ratio over N")


_ = ax.plot(taxi_priorities_rand.groupby("batch")[["avg_greedy_ratio"]].mean(),
        color="orange",
        label="Avg Greedy Taxi Cost Ratio over N")

_ = ax.legend()
```

```
# set y domain to 0-500

#_ = ax.set_ylim(20, 50)

# setear xticks a [0-10], [10-20], [20-30], etc
# [f"[{i}-{i+10}]" for i in range(0, 500, 10)]

_ = ax.set_xticks(range(0, 50, 1))

_ = ax.set_xticklabels([f"[{i}-{i+10}]" for i in range(0, 500, 10)])

# ylim 0-300

_ = ax.set_ylim(0, 300)

fig.suptitle("Comparacion de Costo de Taxistas vs. Cantidad de pasajeros/taxis en Instancias Aleatorias - Agrupadas en intervalos de 10", fontsize=24)

plt.savefig("../output/figures/taxi_priorities_random_grouped.png")
```

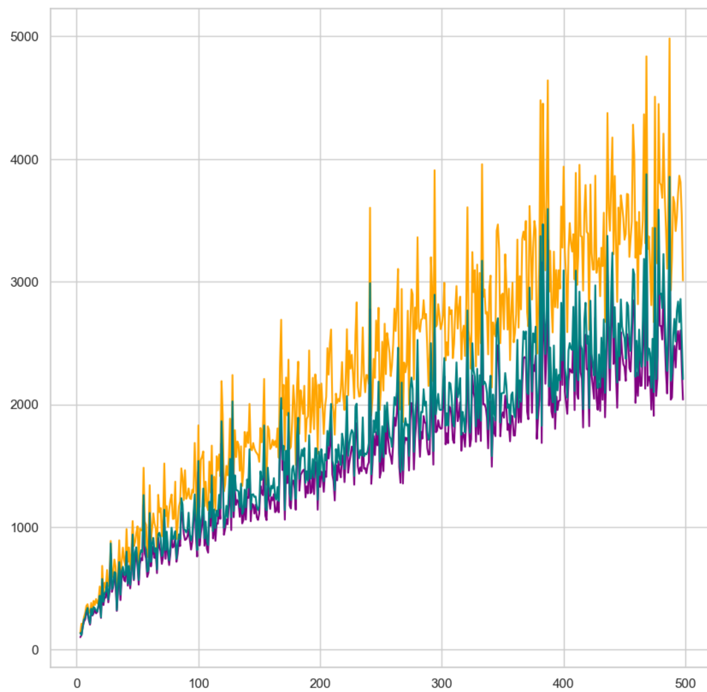



[ ]:
```
ad_hoc_solutions["greedy_cost"] = ad_hoc_solutions["greedy_cost"].apply(lambda x: float(x))
ad_hoc_solutions["min_cost_flow_cost"] = ad_hoc_solutions["min_cost_flow_cost"].apply(lambda x: float(x))
ad_hoc_solutions["priority_cost"] = ad_hoc_solutions["priority_cost"].apply(lambda x: float(x))

fig, ax = plt.subplots(figsize=(10, 10))

_ = ax.plot(ad_hoc_solutions.groupby("n")[["greedy_cost"]].mean(),
        color="orange",
        label="Avg Greedy Cost over N")

_ = ax.plot(ad_hoc_solutions.groupby("n")[["min_cost_flow_cost"]].mean(),
        color="purple",
```

```
        label="Avg Min Cost Flow Cost over N")

_ = ax.plot(ad_hoc_solutions.groupby("n")[["priority_cost"]].mean(),
        color="teal",
        label="Avg Priority Cost over N")

fig.suptitle("Comparacion de Valor Objetivo vs. Cantidad de pasajeros/taxis en␣
↪Instancias Aleatorias", fontsize=24)

#plt.savefig("../output/figures/solutions_random.png")
```

[ ]: Text(0.5, 0.98, 'Comparacion de Valor Objetivo vs. Cantidad de pasajeros/taxis en Instancias Aleatorias')

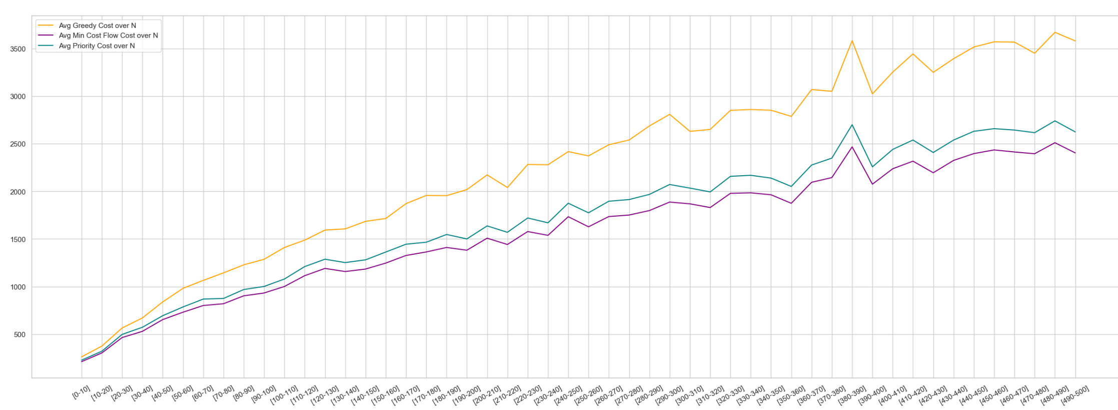
Comparacion de Valor Objetivo vs. Cantidad de pasajeros/taxis en Instancias Aleatorias




[ ]:
```
fig, ax = plt.subplots(figsize=(30, 10))

# batch by 10

ad_hoc_solutions["batch"] = ad_hoc_solutions["n"].apply(lambda x: x // 10)

_ = ax.plot(ad_hoc_solutions.groupby("batch")[["greedy_cost"]].mean(),
        color="orange",
```

```
        label="Avg Greedy Cost over N")

_ = ax.plot(ad_hoc_solutions.groupby("batch")[["min_cost_flow_cost"]].mean(),
        color="purple",
        label="Avg Min Cost Flow Cost over N")

_ = ax.plot(ad_hoc_solutions.groupby("batch")[["priority_cost"]].mean(),
        color="teal",
        label="Avg Priority Cost over N")

ax.set_xticks(range(0, 50, 1))
ax.set_xticklabels([f"[{i}-{i+10}]" for i in range(0, 500, 10)])

#rotate xticks

for tick in ax.get_xticklabels():
        tick.set_rotation(30)

_ = ax.legend()

fig.suptitle("Comparacion de Valor Objetivo vs. Cantidad de pasajeros/taxis en␣
 ↪Instancias Aleatorias", fontsize=24)

plt.savefig("../output/figures/solutions_random.png")
```

Comparacion de Valor Objetivo vs. Cantidad de pasajeros/taxis en Instancias Aleatorias

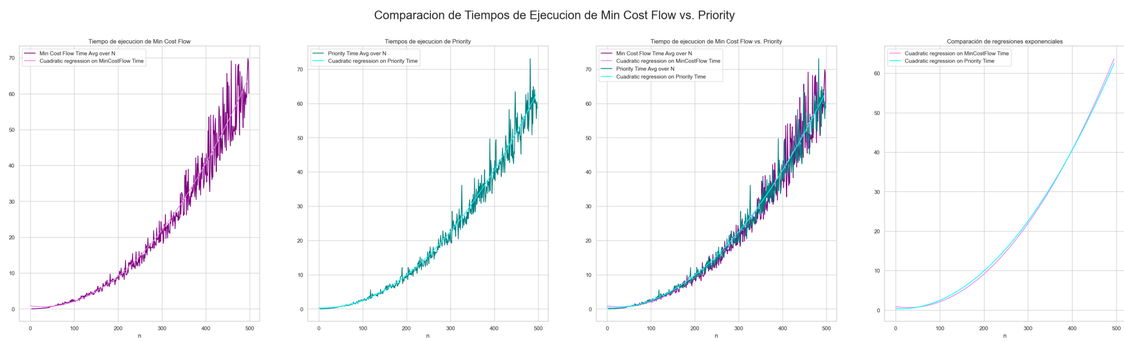



[ ]:
```
# Comparación temporal de soluciones Prioridad vs. Min Cost Flow

# Analisis de tiempo de ejecucion

ad_hoc_solutions["priority_time"] = ad_hoc_solutions["priority_time"].
 ↪apply(lambda x: float(x))
```

```python
ad_hoc_solutions["min_cost_flow_time"] = ad_hoc_solutions["min_cost_flow_time"].
↪apply(lambda x: float(x))

# Plot time vs. n

fig, axs = plt.subplots(1, 4, figsize=(40, 10))

min_cost_flow_times = ad_hoc_solutions.groupby("n")[["min_cost_flow_time"]].
↪mean()
priority_times = ad_hoc_solutions.groupby("n")[["priority_time"]].mean()

"""
ax.plot(greedy_times,
        color="teal",
        label="Greedy Time Avg over N")
 """

axs[0].plot(min_cost_flow_times,
        color="purple",
        label="Min Cost Flow Time Avg over N")

# Cuadratic regression of min_cost_flow_time

exp_reg = np.poly1d(np.polyfit(min_cost_flow_times.index,␣
↪min_cost_flow_times["min_cost_flow_time"], 2))

exp_reg_vals = exp_reg(min_cost_flow_times.index)

axs[0].plot(exp_reg_vals,
        color="Violet",
        label="Cuadratic regression on MinCostFlow Time")

axs[0].set_title("Tiempo de ejecucion de Min Cost Flow")
axs[0].set_xlabel("n")

_ = axs[0].legend()

axs[1].plot(priority_times,
        color="teal",
        label="Priority Time Avg over N")

# Cuadratic regression of priority_time

exp_reg_pri = np.poly1d(np.polyfit(priority_times.index,␣
↪priority_times["priority_time"], 2))
exp_reg_pri_vals = exp_reg_pri(priority_times.index)
```

```python
axs[1].plot(exp_reg_pri_vals,
        color="cyan",
        label="Cuadratic regression on Priority Time")

axs[1].set_title("Tiempos de ejecucion de Priority")

axs[1].set_xlabel("n")

_ = axs[1].legend()


axs[2].plot(min_cost_flow_times,
        color="purple",
        label="Min Cost Flow Time Avg over N")

axs[2].plot(exp_reg_vals,
        color="Violet",
        label="Cuadratic regression on MinCostFlow Time")

axs[2].plot(priority_times,
        color="teal",
        label="Priority Time Avg over N")

axs[2].plot(exp_reg_pri_vals,
        color="cyan",
        label="Cuadratic regression on Priority Time")

axs[2].set_title("Tiempo de ejecucion de Min Cost Flow vs. Priority")

axs[2].set_xlabel("n")

_ = axs[2].legend()


axs[3].plot(exp_reg_vals,
        color="Violet",
        label="Cuadratic regression on MinCostFlow Time")

axs[3].plot(exp_reg_pri_vals,
        color="cyan",
        label="Cuadratic regression on Priority Time")

axs[3].set_title("Comparación de regresiones exponenciales")

axs[3].set_xlabel("n")

_ = axs[3].legend()
```

```
fig.suptitle("Comparacion de Tiempos de Ejecucion de Min Cost Flow vs.␣
  ↪Priority", fontsize=24)

fig.savefig("../output/figures/time_comparison_priority_vs_min_cost_flow.png")
```




[ ]:

```

```