R2_report_feature_analyze

May 12, 2024

1 Reporte de Resultados

1.0.1 Metodología:

En esta documento comparamos experimentos realizados sobre el dataset de 'leukemia' en su version original y aumentada:

Grupo de experimentos con dataset original.

- '0001' utilizando dataset original, cromosoma activo 0.1, alpha 0.5, 30 pruebas.
- '0012' realizado con dataset original, cromosoma activo 0.01 y alpha 0.5, 30 pruebas.
- '0013' realizado con dataset original, cromosoma activo 0.005 y alpha 0.5, 30 pruebas.

Grupo de experimentos con dataset aumentado.

- '0002' realizado con dataset aumentado en 100 observaciones mediante un VAE, cromosoma activo 0.1, alpha 0.5, 30 pruebas.
- '0003' realizado con dataset aumentado en 1000 observaciones mediante un VAE, cromosoma activo 0.1, alpha 0.5, 30 pruebas.
- '0006' realizado con dataset aumentado en 100 observaciones mediante un VAE, cromosoma activo 0.01 y alpha 0.3, 10 pruebas.
- '0007' realizado con dataset aumentado en 100 observaciones mediante un VAE, cromosoma activo 0.01 y alpha 0.5, 10 pruebas.
- '0008' realizado con dataset aumentado en 100 observaciones mediante un VAE, cromosoma activo 0.01 y alpha 0.2, 30 pruebas.

- '0009' realizado con dataset aumentado en 100 observaciones mediante un VAE, cromosoma activo 0.01 y alpha 0.5, 30 pruebas.
- '0011' realizado con dataset aumentado en 100 observaciones mediante un VAE, cromosoma activo 0.005 y alpha 0.5, 30 pruebas.

```
[]: data = pd.read_csv('experiments_results.csv')
Г1:
     data.tail(3)
[]:
                                                               description \
                experiment_name
                                        date
          leukemia_base_0012_27
     253
                                  2024-05-12 multiexperiments_small_gene
          leukemia base 0012 28
                                  2024-05-12 multiexperiments small gene
     254
     255
          leukemia_base_0012_29
                                  2024-05-12 multiexperiments_small_gene
                 current_dir POP_SIZE
                                         PROB MUT
                                                          GMAX
                                                                DAT SIZE
                                                     PX
     253
          /root/ealab/expga1
                                    100
                                                 1
                                                   0.75
                                                            20
                                                                      38
     254
          /root/ealab/expga1
                                    100
                                                 1
                                                    0.75
                                                            20
                                                                      38
          /root/ealab/expga1
                                    100
     255
                                                 1
                                                    0.75
                                                            20
                                                                      38
          all_features_fitness
                                 all_feature_ngenes
                                                     all_feature_acc elite_fitness
     253
                          0.456
                                               7129
                                                                0.912
                                                                                0.996
     254
                          0.456
                                               7129
                                                                0.912
                                                                                0.995
     255
                          0.456
                                               7129
                                                                0.912
                                                                                0.996
          elite_ngenes
                        elite_acc
                                   pob_fitness_avg
                                                     pob_accuracy_avg
     253
                    57
                               1.0
                                              0.996
                                                                   1.0
                                              0.995
                                                                   1.0
     254
                    65
                               1.0
     255
                    51
                               1.0
                                              0.996
                                                                   1.0
                          pob_fitness_std pob_accuracy_std pob_ngenes_std \
          pob_ngenes_avg
     253
                    57.0
                                       0.0
                                                          0.0
                                                                           0.0
     254
                    65.0
                                       0.0
                                                          0.0
                                                                           0.0
     255
                    51.0
                                       0.0
                                                          0.0
                                                                           0.0
                           pob_accuracy_max
          pob_fitness_max
                                              pob_ngenes_max
     253
                    0.996
                                                           57
                                         1.0
     254
                    0.995
                                         1.0
                                                           65
     255
                    0.996
                                                           51
                                         1.0
    data.columns
[]:
[]: Index(['experiment_name', 'date', 'description', 'current_dir', 'POP_SIZE',
            'PROB_MUT', 'PX', 'GMAX', 'DAT_SIZE', 'all_features_fitness',
            'all_feature_ngenes', 'all_feature_acc', 'elite_fitness',
            'elite_ngenes', 'elite_acc', 'pob_fitness_avg', 'pob_accuracy_avg',
            'pob_ngenes_avg', 'pob_fitness_std', 'pob_accuracy_std',
            'pob_ngenes_std', 'pob_fitness_max', 'pob_accuracy_max',
```

Experimentos excluidos Excluiremos del análisis experimentos con menos de 30 pruebas, para que la comparación de resultados entre dataset original y aumentado sea en igualdad de condiciones. Excluimos el experimento 0008 porque corresponde a la exploración de una configuración extrema del parámetro alpha, y no es representativo de la configuración general de los experimentos.

2 Resultados

'pob_ngenes_max'],

2.1 Gráfico de resultado de las distintas pruebas en cada experimento

Hemos trabajando con la configuración del cromosoma activo con valores 0.1, 0.01 y 0.005, y con el parámetro alpha para el cálculo de fitness en valores 0.3 y 0.5.

```
[]: import matplotlib.pyplot as plt

# Factorize the 'experiment_group' to get labels and unique ids
groups, labels = pd.factorize(leukemias['experiment_group'])

# Set up the matplotlib figure and axes for two subplots
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(14, 6), sharey=True)

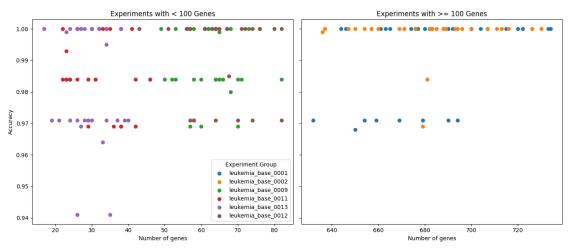
# Define the condition for splitting the data
condition = leukemias['pob_ngenes_avg'] < 100

# Plot for 'pob_ngenes_avg' below 100
for i, label in enumerate(labels):
    group_data = leukemias[(groups == i) & condition]</pre>
```

```
axes[0].scatter(group_data['pob_ngenes_avg'],__

¬group_data['pob_accuracy_avg'], label=label)
axes[0].set_title('Experiments with < 100 Genes')</pre>
axes[0].set xlabel('Number of genes')
axes[0].set_ylabel('Accuracy')
# Plot for 'pob_ngenes_avg' above 100
for i, label in enumerate(labels):
    group_data = leukemias[(groups == i) & ~condition]
    axes[1].scatter(group_data['pob_ngenes_avg'],__

¬group_data['pob_accuracy_avg'], label=label)
axes[1].set_title('Experiments with >= 100 Genes')
axes[1].set_xlabel('Number of genes')
#axes[1].set_ylabel('Accuracy') # No need to set again, shared y-axis
# Add a legend to the first subplot (or to both if necessary)
axes[0].legend(title="Experiment Group")
# axes[1].legend(title="Experiment Group") # Optional: add if needed for
 \hookrightarrow clarity
# Show plot
plt.tight_layout() # Adjust layout to not overlap
plt.show()
```



```
[]: # Define original data group

original_data = ['leukemia_base_0001', 'leukemia_base_0012',

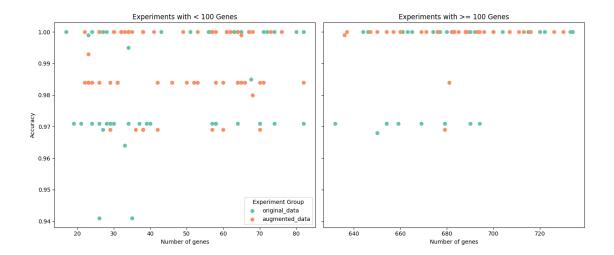
□ 'leukemia_base_0013']

# set the same palette for all plots

sns.set_palette("Set2")
```

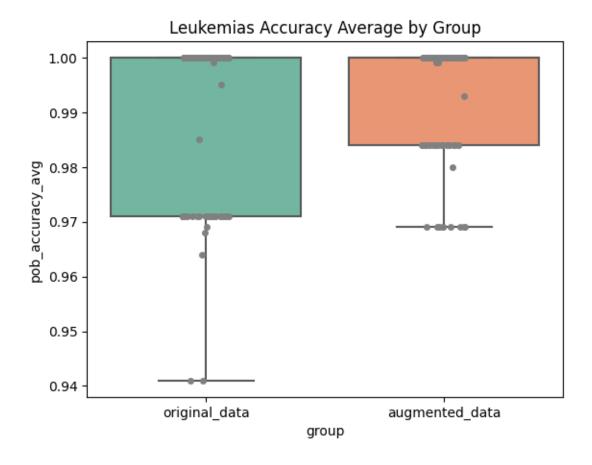
```
# Determine which group each experiment belongs to
leukemias['group'] = leukemias['experiment group'].apply(lambda x:
 # Factorize the new 'group' column to get labels and unique ids
groups, labels = pd.factorize(leukemias['group'])
# Set up the matplotlib figure and axes for two subplots
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(14, 6), sharey=True)
# Define the condition for splitting the data
condition = leukemias['pob_ngenes_avg'] < 100</pre>
# Plot for 'pob_ngenes_avg' below 100
for i, label in enumerate(labels):
   group data = leukemias[(groups == i) & condition]
   axes[0].scatter(group_data['pob_ngenes_avg'],_

¬group_data['pob_accuracy_avg'], label=label)
axes[0].set_title('Experiments with < 100 Genes')</pre>
axes[0].set_xlabel('Number of genes')
axes[0].set_ylabel('Accuracy')
# Plot for 'pob_ngenes_avg' above 100
for i, label in enumerate(labels):
   group_data = leukemias[(groups == i) & ~condition]
   axes[1].scatter(group data['pob ngenes avg'],
⇒group_data['pob_accuracy_avg'], label=label)
axes[1].set title('Experiments with >= 100 Genes')
axes[1].set_xlabel('Number of genes')
#axes[1].set ylabel('Accuracy') # No need to set again, shared y-axis
# Add a legend to the first subplot (or to both if necessary)
axes[0].legend(title="Experiment Group")
# axes[1].legend(title="Experiment Group") # Optional: add if needed for
 \hookrightarrow clarity
# Show plot
plt.tight_layout() # Adjust layout to not overlap
plt.show()
```



2.2 Gráfico de resultados por grupo de experimentos

```
[]: # plot the leukemias accuracy average by group
# set the same palette for all plots
sns.set_palette("Set2")
sns.boxplot(x='group', y='pob_accuracy_avg', data=leukemias)
# add data point in grey
sns.stripplot(x='group', y='pob_accuracy_avg', data=leukemias, color='grey')
plt.title('Leukemias Accuracy Average by Group')
plt.show()
```



```
[]: # Create a sort order to organize groups together
    sort_order = sorted(leukemias['experiment_group'].unique(), key=lambda x:__
     # set the same palette for all plots
    sns.set_palette("Set2")
    # Set up the matplotlib figure for the scatter plots and boxplot
    fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(21, 6), sharey=True)
    # Scatter plot for 'pob_ngenes_avg' below 100
    for i, label in enumerate(pd.unique(leukemias['group'])):
        group_data = leukemias[(leukemias['group'] == label) & condition]
        axes[0].scatter(group_data['pob_ngenes_avg'],__
     ⇒group_data['pob_accuracy_avg'], label=label)
    axes[0].set_title('Experiments with < 100 Genes')</pre>
    axes[0].set_xlabel('Number of genes')
    axes[0].set_ylabel('Accuracy')
    # Scatter plot for 'pob_ngenes_avg' above 100
```

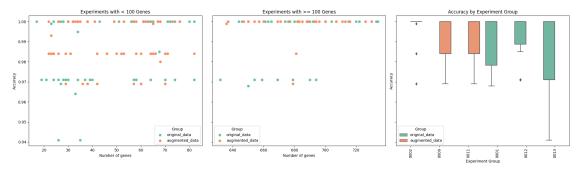
```
for i, label in enumerate(pd.unique(leukemias['group'])):
          group_data = leukemias[(leukemias['group'] == label) & ~condition]
          axes[1].scatter(group_data['pob_ngenes_avg'],__

¬group_data['pob_accuracy_avg'], label=label)
axes[1].set_title('Experiments with >= 100 Genes')
axes[1].set xlabel('Number of genes')
# Box plot grouped by experiment group and colored by 'original_data' and
  → 'augmented_data'
sns.boxplot(x='experiment_group', y='pob_accuracy_avg', hue='group', u

data=leukemias, palette="Set2", ax=axes[2], order=sort_order)

→ data=leukemias, palette="Set2", ax=axes[2], order=sort_order]

→ data=leukemias, palette=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort_order=sort
axes[2].set_title('Accuracy by Experiment Group')
axes[2].set_xlabel('Experiment Group')
axes[2].set_ylabel('Accuracy') # We can repeat the label here for clarity on_
   ⇔the new plot
# set x lebels in 90 degree
axes[2].tick_params(axis='x', rotation=90)
#axes[2].set xticklabels([]) # Hide x-axis labels to prevent overlap
# truncated the labels to the last 4 characters
axes[2].set_xticklabels([label[-4:] for label in sort_order])
# Adjust legend for all plots
axes[0].legend(title="Group")
axes[1].legend(title="Group")
axes[2].legend(title="Group", loc='lower left') # Adjust the location of the
   → legend if necessary
# Show plot
plt.tight_layout() # Adjust layout to not overlap
plt.show()
```



2.3 Obaservación 1

Entendemos que los gráficos anteriores muestran un patron: para los experimentos con datos aumentados tenemos una menor dispersión en los resultados, y una tendencia a obtener mejores

resultados en comparación con los experimentos con datos originales.

3 Exploración de la selección de características

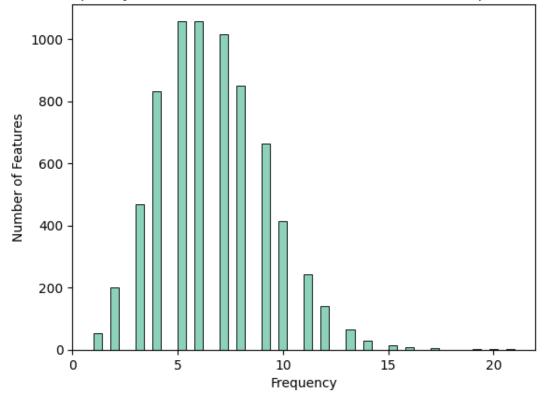
En esta sección exploramos la selección de características en los experimentos buscando diferenciar entre los experimentos con datos originales y aumentados.

```
[]: # Replace 'your_file.json' with the path to your JSON file
with open('experiments.json', 'r') as file:
    features = json.load(file)
```

```
[]: for key, value in list(features.items())[:2]:
         print(f'Experiment: {key}')
         common_genome_all_prob = value['common_genome_all_prob']
         common_genome_bin = value['common_genome_bin']
         common_genome_bin_sum = value['common_genome_bin_sum']
         common genome prob sum = value['common genome prob sum']
         selected features bin = value['selected features bin']
         selected features prob = value['selected features prob']
                     common genome: {common_genome_all_prob[:20]}')
         print(f'
                     common genome len: {len(common_genome_all_prob)}')
         print(f'
                    common genome bin: {common_genome_bin[:20]}')
         print(f'
                    common genome bin len: {len(common_genome_bin)}')
         print(f'
                     common genome bin sum: {common_genome_bin_sum}')
         print(f'
                    common genome prob sum: {common_genome_prob_sum}')
         print(f'
                     selected features bin: {selected_features_bin[:3]}')
         print(f'
         print(f'
                     selected features prob: {selected_features_prob[:3]}')
```

```
common genome bin len: 7129
       common genome bin sum: 680
       common genome prob sum: 680
       selected features bin: ['AFFX-BioB-3_at', 'AFFX-ThrX-5_at', 'AFFX-
   ThrX-3 at']
       selected features prob: ['AFFX-BioB-3_at', 'AFFX-ThrX-5_at', 'AFFX-
   ThrX-3 at']
   Experiment: leukemia_base_0001_1
       0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0]
       common genome len: 7129
       0]
       common genome bin len: 7129
       common genome bin sum: 700
       common genome prob sum: 700
       selected features bin: ['AFFX-TrpnX-5_at', 'AFFX-HUMISGF3A/M97935_MB_at',
    'AFFX-HUMGAPDH/M33197_5_at']
       selected features prob: ['AFFX-TrpnX-5_at', 'AFFX-HUMISGF3A/M97935_MB_at',
    'AFFX-HUMGAPDH/M33197 5 at']
   3.1 Feature Frequency by Experiments
[]: result_acc_features = []
    for key, value in features.items():
       result = {}
       selected_features_bin = value['selected_features_bin']
       experiment name = key
       result = {'experiment_name': experiment_name, 'selected_features_bin': __
     ⇒selected_features_bin}
       result_acc_features.append(result)
[]: # Create a DataFrame from the list of dictionaries and add form 'data' the
     Golumns 'pob_accuracy_avg' and 'pob_ngenes_avg' using the 'experiment_name'
     ⇔as key
    result_acc_features = pd.DataFrame(result_acc_features)
    result_acc_features = result_acc_features.merge(data[['experiment_name',_
     []: result_acc_features.head(3)
                                                   selected_features_bin \
[]:
           experiment_name
    0 leukemia_base_0001_0 [AFFX-BioB-3_at, AFFX-ThrX-5_at, AFFX-ThrX-3_a...
    1 leukemia_base_0001_1 [AFFX-TrpnX-5_at, AFFX-HUMISGF3A/M97935_MB_at,...
    2 leukemia_base_0001_2 [AFFX-BioC-3_at, AFFX-CreX-3_st, AFFX-PheX-5_a...
```

Frequency Distribution of Selected Features accross Experiments



```
[]: # create a new column group with the first 18 letters of the experiment name
    result_acc_features['group'] = result_acc_features['experiment_name'].
      →apply(lambda x: x[:18])
[]: leukemia comparables = [
         'leukemia base 0001',
         'leukemia_base_0002',
         'leukemia_base_0009',
         'leukemia_base_0011',
         'leukemia_base_0012',
         'leukemia_base_0013',
    # filter the data to only include the leukemia_comparables
    result_acc_features = result_acc_features[result_acc_features['group'].
      ⇔isin(leukemia_comparables)]
    result_acc_features['group'].value_counts()
[]: group
    leukemia_base_0001
                          30
    leukemia base 0002
                           30
    leukemia_base_0009
                          30
    leukemia base 0011
                           30
    leukemia_base_0013
                           30
    leukemia base 0012
                           30
    Name: count, dtype: int64
[]: | # split the result_acc_feautures into two groups: original_data and_
     →augmented_data based on the list original_data
    original_data = ['leukemia_base_0001', 'leukemia_base_0012',_
      result_acc_features['condition'] = result_acc_features['group'].apply(lambda x:__
     ⇔'original_data' if x in original_data else 'augmented_data')
    result_acc_features_original =__
      Gresult_acc_features[result_acc_features['condition'] == 'original data']
    result acc features augmented = ____
      Gresult_acc_features[result_acc_features['condition'] == 'augmented_data']
[]: # create a list of element and count the number of elements in the list
    print(pd.Series([x[:18] for x in result_acc_features_original['group']]).
      →value_counts())
    print(pd.Series([x[:18] for x in result acc features augmented['group']]).
      →value counts())
    leukemia base 0001
                          30
    leukemia base 0013
                          30
    leukemia_base_0012
    Name: count, dtype: int64
```

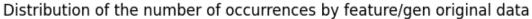
```
leukemia_base_0002 30
leukemia_base_0009 30
leukemia_base_0011 30
Name: count, dtype: int64
```

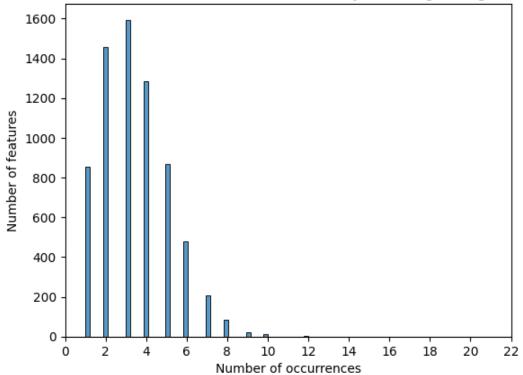
4 Original Dataset

```
[]: # expand the 'selected_features_bin' column into multiple rows
     result_acc_features_original_long = result_acc_features_original.
      ⇔explode('selected_features_bin')
[]: # group by the 'selected_features_bin', count the number of occurrence and_
      seconcatenate the 'experiment name' and 'pob_accuracy_avg' columns
     result_acc_features_wide_original = result_acc_features_original_long.

¬groupby('selected_features_bin').agg(
         experiment_name=('experiment_name', lambda x: ', '.join(x)),
         # create a list with the 'pob_accuracy_avg' values
         pob_accuracy_avg=('pob_accuracy_avg', list),
         # crate a list with the 'pob_ngenes_avg' values
         pob_ngenes_avg=('pob_ngenes_avg', list),
         count=('experiment_name', 'count')
     ).reset_index()
[]: result_acc_features_wide_original.sort_values('count', ascending=False).head(3)
[]:
          selected_features_bin
                                                                    experiment_name \
                    ACO02464_at leukemia_base_0001_1, leukemia_base_0001_4, le...
     60
     4624
                    U59632_s_at leukemia_base_0001_2, leukemia_base_0001_5, le...
     2361
                      M19507_at leukemia_base_0001_15, leukemia_base_0001_18, ...
                                            pob_accuracy_avg \
     60
           [1.0, 0.971, 1.0, 1.0, 1.0, 1.0, 0.971, 1.0, 1...
           [1.0, 1.0, 1.0, 0.968, 1.0, 1.0, 1.0, 0.971, 1...
     4624
     2361 [1.0, 1.0, 1.0, 0.971, 0.969, 1.0, 1.0, 1.0, 1...
                                              pob_ngenes_avg count
           [700.0, 654.0, 692.0, 661.0, 720.0, 676.0, 632...
     60
                                                                12
           [674.0, 688.0, 677.0, 650.0, 682.0, 720.0, 690...
     4624
                                                                12
           [720.0, 690.0, 17.0, 29.0, 27.0, 61.0, 56.0, 6...
                                                                11
[]: # print the columns data types
     result acc features wide original.shape
[]: (6869, 5)
```

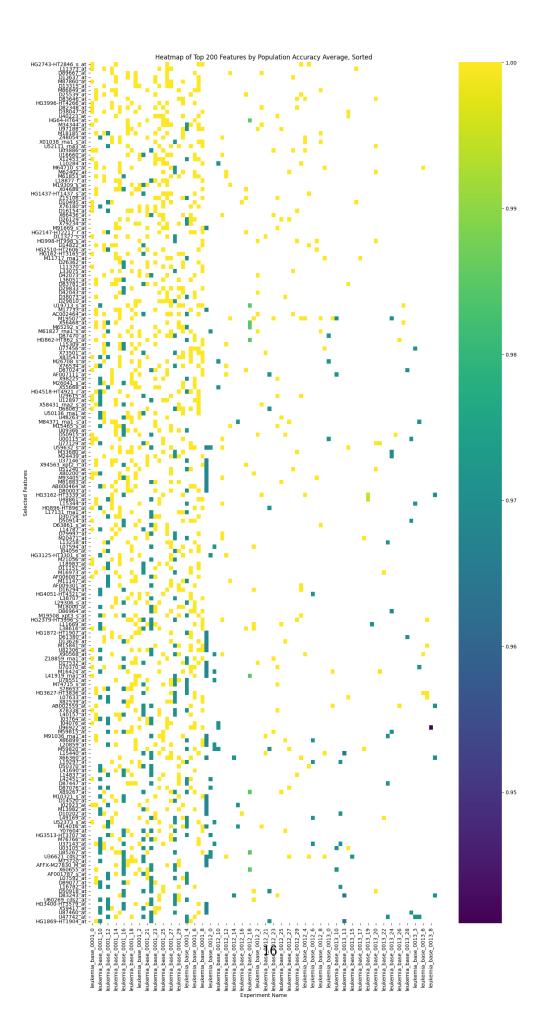
```
[]: # save the result to a csv file result_acc_features_wide_original.to_csv('features_occurrence_original.csv', □ →index=False)
```





4.1 Gráfico de frecuencia de selección de características en los experimentos con dataset original

```
[]: # Assuming the DataFrame is already loaded as df
     df = result_acc_features_wide_original
     # Filter the top 50 features by 'count'
     top_features = df.nlargest(200, 'count')
     # Expand the 'pob_accuracy_avq' and 'experiment_name' into individual rows
     expanded_rows = []
     for index, row in top_features.iterrows():
         accuracies = row['pob_accuracy_avg']
         experiment_names = row['experiment_name'].split(', ')
         if isinstance(accuracies, str):
             accuracies = eval(accuracies)
         for accuracy, exp name in zip(accuracies, experiment names):
             if 'leukemia_base_0008' not in exp_name.strip():
                 expanded_rows.append({
                     'selected_features_bin': row['selected_features_bin'],
                     'pob_accuracy_avg': accuracy,
                     'experiment_name': exp_name.strip()
                 })
     expanded_df = pd.DataFrame(expanded_rows)
     # Create a pivot table for the heatmap
     pivot_table = expanded_df.pivot_table(index='selected_features_bin',_
      ⇔columns='experiment_name', values='pob_accuracy_avg', aggfunc='mean')
     average_accuracy = pivot_table.mean(axis=1).sort_values(ascending=False)
     sorted_pivot_table = pivot_table.loc[average_accuracy.index]
     # Plot heatmap without annotations and sorted by average accuracy
     plt.figure(figsize=(15, 30)) # Adjust the size accordingly
     sns.heatmap(sorted_pivot_table, annot=False, cmap='viridis')
     plt.title('Heatmap of Top 200 Features by Population Accuracy Average, Sorted')
     plt.xlabel('Experiment Name')
     # adjust the y-axis to include all the features
     plt.yticks(np.arange(0.5, len(sorted_pivot_table), 1), sorted_pivot_table.index)
     plt.ylabel('Selected Features')
     # Save the plot to a file
     plt.savefig('heatmap_top200_features_original.png', format='png', dpi=300) #_J
      →You can specify another path or format like 'pdf'
     plt.show()
```



5 Augmented Dataset

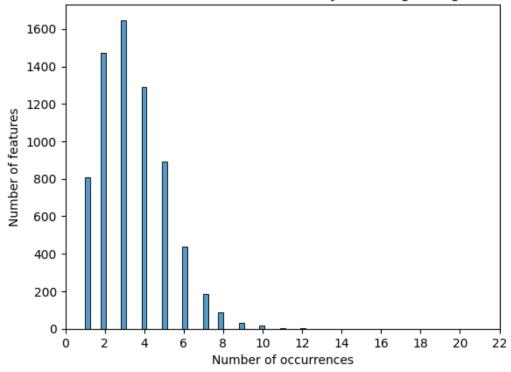
```
[]: # expand the 'selected features bin' column into multiple rows
    result_acc_features_augmented_long = result_acc_features_augmented.
      ⇔explode('selected_features_bin')
    result_acc_features_augmented_long.head(3)
[]:
             experiment_name selected_features_bin pob_accuracy_avg \
    30 leukemia_base_0002_0
                                                              1.0
                                   AFFX-BioB-M_st
    30
        leukemia base 0002 0
                                   AFFX-BioC-5 st
                                                              1.0
        leukemia_base_0002_0
                                   AFFX-CreX-3_st
                                                              1.0
        pob_ngenes_avg
                                               condition
                                   group
                685.0 leukemia_base_0002 augmented_data
    30
    30
                685.0 leukemia_base_0002 augmented_data
                685.0 leukemia_base_0002 augmented_data
    30
[]: # group by the 'selected features bin', count the number of occurrence and
     seconcatenate the 'experiment_name' and 'pob_accuracy_avg' columns
    result acc features wide augmented = result acc features augmented long.

¬groupby('selected_features_bin').agg(
        experiment name=('experiment_name', lambda x: ', '.join(x)),
        # create a list with the 'pob_accuracy_avg' values
        pob_accuracy_avg=('pob_accuracy_avg', list),
        # crate a list with the 'pob_ngenes_avg' values
        pob ngenes avg=('pob ngenes avg', list),
        count=('experiment_name', 'count')
    ).reset index()
[]: result_acc_features_wide_augmented.sort_values('count', ascending=False).head(3)
[]:
         selected_features_bin
                                                               experiment_name \
                  M20203_s_at leukemia_base_0002_3, leukemia_base_0002_7, le...
    2387
    5861
                    X66362_at leukemia_base_0002_0, leukemia_base_0002_7, le...
                    X55668_at leukemia_base_0002_0, leukemia_base_0002_2, le...
    5650
                                         pob_accuracy_avg \
    2387
          5861
          [1.0, 1.0, 1.0, 1.0, 1.0, 0.969, 1.0, 1.0...
    5650
          pob ngenes avg count
          [660.0, 682.0, 657.0, 700.0, 689.0, 730.0, 683...
    2387
                                                           14
```

```
[685.0, 682.0, 694.0, 696.0, 650.0, 730.0, 679...
     5861
                                                               12
     5650
           [685.0, 683.0, 660.0, 669.0, 637.0, 671.0, 654...
                                                               12
[]: # print the columns data types
     result_acc_features_wide_augmented.shape
[]: (6876, 5)
[]: # save the result to a csv file
     result_acc_features_wide_augmented.to_csv('features_occurrence_augmented.csv',u
      →index=False)
[]: # plot the distribution of the count column
     sns.histplot(result_acc_features_wide_augmented['count'], bins=50)
     # make the x-axis integer values
     plt.xticks(np.arange(0, 23, 2))
     # set the x-axis label
     plt.xlabel('Number of occurrences')
     # set the y-axis label
     plt.ylabel('Number of features')
     # show the plot
     # title of the plot
     plt.title('Distribution of the number of occurrences by feature/gen augmented ⊔

data¹)
     plt.show()
```





5.1 Gráfico de frecuencia de selección de características en los experimentos con dataset aumentado

```
'pob_accuracy_avg': accuracy,
                'experiment_name': exp_name.strip()
            })
expanded_df = pd.DataFrame(expanded_rows)
# Create a pivot table for the heatmap
pivot_table = expanded_df.pivot_table(index='selected_features_bin',__
 ⇔columns='experiment_name', values='pob_accuracy_avg', aggfunc='mean')
average_accuracy = pivot_table.mean(axis=1).sort_values(ascending=False)
sorted_pivot_table = pivot_table.loc[average_accuracy.index]
# Plot heatmap without annotations and sorted by average accuracy
plt.figure(figsize=(15, 30)) # Adjust the size accordingly
sns.heatmap(sorted_pivot_table, annot=False, cmap='viridis')
plt.title('Heatmap of Top 200 Features by Population Accuracy Average, Sorted')
plt.xlabel('Experiment Name')
# adjust the y-axis to include all the features
plt.yticks(np.arange(0.5, len(sorted_pivot_table), 1), sorted_pivot_table.index)
plt.ylabel('Selected Features')
# Save the plot to a file
plt.savefig('heatmap_top200_features_augmented.png', format='png', dpi=300) #_U
 →You can specify another path or format like 'pdf'
plt.show()
```

