Final Project : Bob Ross

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Data Set Description

I chose the Bob Ross dataset from fivethirtyeight's GitHub repo: https://github.com/fivethirtyeight/data/tree/master/bob-ross

This dataset revolves around Bob Ross' television show, "The Joy of Painting", which aired from 1983 to 1994. Bob Ross painted a total of 381 works while featured guests created an additional 22 paintings for a grand total of 403 paintings over 11 years of airtime.

The creator of this dataset, Walt Hickey, analyzed every episode of Bob Ross' show and generated 67 keywords which described content (trees, water, mountains, clouds, etc.), frame choices, guest artists, and even structures, for a total for 3,224 tags.

I did not read Walt Hickey's analysis until after writing this report.

Initial Data Exploration Plan

My initial plan was to understand the following dataset attributes:

1. The shape of the dataset: `(403, 69)`
2. What features/attributes were in the dataset: 69 different keywords
3. How the dataset was formatted: Categorical, binary-encoded

```
data_filename = './data/elements-by-episode.csv'
initial_df = pd.read_csv(data_filename)
initial_df.shape()
initial_df.columns
initial_df.head()

--- Output ---
```

```
(403, 69)

Index(['EPISODE', 'TITLE', 'APPLE_FRAME', 'AURORA_BOREALIS', 'BARN', 'BEACH',
       'BOAT', 'BRIDGE', 'BUILDING', 'BUSHES', 'CABIN', 'CACTUS',
       'CIRCLE_FRAME', 'CIRRUS', 'CLIFF', 'CLOUDS', 'CONIFER', 'CUMULUS',
       'DECIDUOUS', 'DIANE_ANDRE', 'DOCK', 'DOUBLE_OVAL_FRAME', 'FARM',
       'FENCE', 'FIRE', 'FLORIDA_FRAME', 'FLOWERS', 'FOG', 'FRAMED', 'GRASS',
       'GUEST', 'HALF_CIRCLE_FRAME', 'HALF_OVAL_FRAME', 'HILLS', 'LAKE',
       'LAKES', 'LIGHTHOUSE', 'MILL', 'MOON', 'MOUNTAIN', 'MOUNTAINS', 'NIGHT',
       'OCEAN', 'OVAL_FRAME', 'PALM_TREES', 'PATH', 'PERSON', 'PORTRAIT',
       'RECTANGLE_3D_FRAME', 'RECTANGULAR_FRAME', 'RIVER', 'ROCKS',
       'SEASHELL_FRAME', 'SNOW', 'SNOWY_MOUNTAIN', 'SPLIT_FRAME', 'STEVE_ROSS',
       'STRUCTURE', 'SUN', 'TOMB_FRAME', 'TREE', 'TREES', 'TRIPLE_FRAME',
       'WATERFALL', 'WAVES', 'WINDMILL', 'WINDOW_FRAME', 'WINTER',
       'WOOD_FRAMED'],
      dtype='object')

EPISODE TITLE APPLE_FRAME AURORA_BOREALIS BARN  BEACH BOAT  BRIDGE  BUILDING  ...
0 S01E01  "A WALK IN THE WOODS" 0 0 0 0 0 0 0 1 ... 0 1 1 0 0 0 0 0 0 0
1 S01E02  "MT. MCKINLEY"  0 0 0 0 0 0 0 0 ... 0 1 1 0 0 0 0 0 1 0
2 S01E03  "EBONY SUNSET"  0 0 0 0 0 0 0 0 ... 0 1 1 0 0 0 0 0 1 0
3 S01E04  "WINTER MIST" 0 0 0 0 0 0 0 1 ... 0 1 1 0 0 0 0 0 0
4 S01E05  "QUIET STREAM"  0 0 0 0 0 0 0 0 ... 0 1 1 0 0 0 0 0 0 0
5 rows × 69 columns
```

Rename Columns to Lowercase

The next step was to change all of the column names to lowercase so I wouldn't have to abuse my caps lock button throughout this project.

```
# Change all column names to lowercase
# This will make it easier to group related features in the next section,
# so I don't have to repeatedly toggle caps lock
lowered_df = initial_df.copy()
lowered_df.columns = initial_df.columns.str.lower()
```

Frequency of Paintings' Features

Now that the data is slightly easier to read and write, let's sort the features and find out which are most commonly seen throughout Bob's paintings.

- We're only looking at the paintings' features here, so it's safe to drop the episode and title features.
- We'll have to transpose the data, meaning swap the axis of the dataset so the rows are indexed by the features and each column is a unique episode.

```
transposed_df = lowered_df.copy()
transposed_df = transposed_df.drop(labels=['episode', 'title'], axis=1)
transposed_df = transposed_df.transpose()
```

	0	1	2	3	4	5	6	7	8	9	...	393	394	395	396	397	398	399	400	401	402
apple_frame	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
aurora_borealis	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
barn	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	1	0
beach	0	0	0	0	0	0	0	0	1	0	...	0	0	0	0	0	0	1	0	0	0
boat	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
waves	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	1	0	0	0
windmill	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
window_frame	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
winter	0	1	1	0	0	1	0	0	0	0	...	0	1	0	0	0	0	0	0	1	0
wood_framed	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0

67 rows × 403 columns

Transposed dataframe

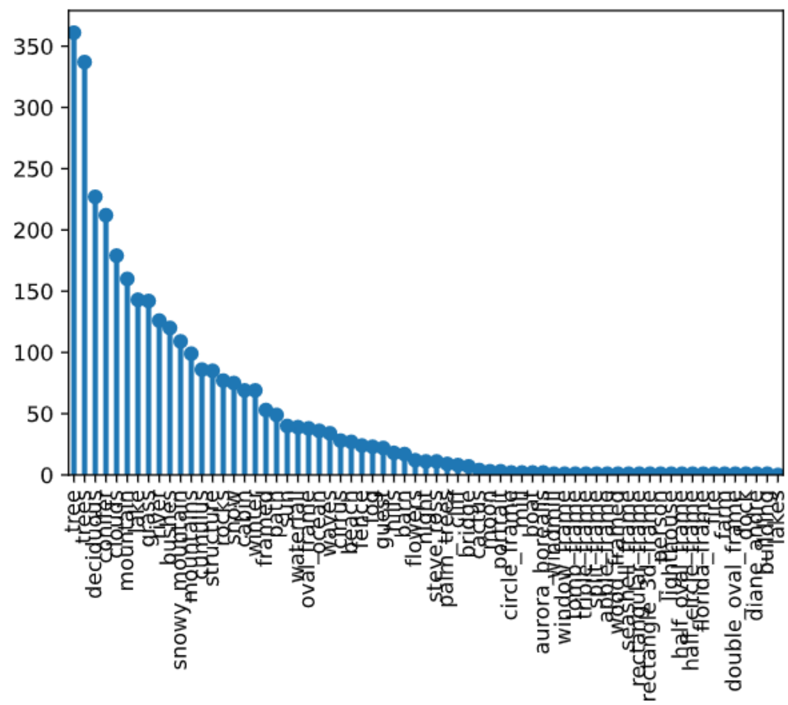
- After transposing the dataframe, we can create a new column named "sum" which aggregates each row (painting feature) using the `sum` function.
  - This will sum all the 1's in the row to give us a grand total per feature.

```
transposed_df['sum'] = transposed_df.agg(func=sum, axis=1)
sum_sorted = transposed_df['sum'].sort_values(ascending=False)
sum_sorted.head(30)

--- Output ---
tree              361
trees             337
deciduous         227
conifer           212
clouds            179
mountain          160
lake              143
grass             142
river             126
bushes            120
snowy_mountain    109
mountains          99
cumulus            86
structure          85
rocks              77
snow               75
cabin              69
winter             69
framed             53
path               49
sun                40
waterfall          39
oval_frame         38
ocean              36
waves              34
cirrus             28
beach              27
fence              24
fog                23
guest              22
Name: sum, dtype: int64
```

As you can see, Bob Ross *loved* to draw trees. Below is a bar plot generated with `sum_sorted.plot.bar()` to show just how much he loved his trees in relation to other features.

- The labels are difficult to read, but we resolve this by grouping features in the Feature Engineering section of this report.



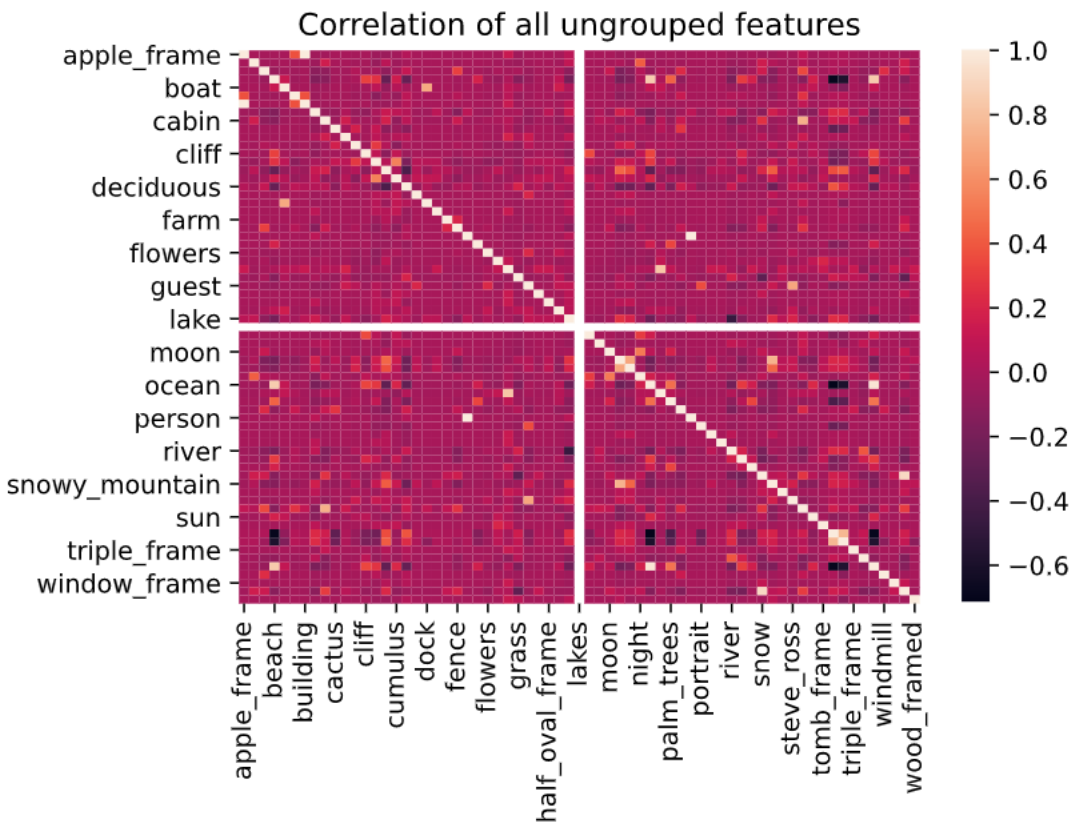
Frequency of each feature

Feature Correlation: Heatmap

Now that we know that Bob Ross loved to paint trees, let's dial in an see if there's some correlation between the painting's features. We'll use `sns.heatmap` to generate a correlation heatmap of all features.

- The **lighter** the pixel, the more **positively correlated** the two features are
- The **darker** the pixel, the more **negatively correlated** the two features are
- NOTE: Not all features are in the axes' labels because it would be crowded and impossible to read. We resolve this later in the Feature Engineering section

```
# Create correlation heatmap of all ungrouped features
corr = lowered_df.corr()
ax = plt.axes()
ax.set(title='Correlation of all ungrouped features')
sns.heatmap(corr)
```



There are a handful of highly positive and negative correlation, let's dive deeper to find what they are

We see in the heatmap that there are a handful of highly positive *and* negative correlations (look for the very light and dark pixels).

Actions taken for data cleaning and feature engineering

As seen above, we ran into graphical issues when trying to plotting correlations between individual features. Let's group our related features in order to reduce clutter in our plots.

Grouping of Related Features

I noticed a lot of the features were related and could be grouped together.

- For example, I could create a group called `group_tree` and add the following features: `group_tree = ['conifer', 'deciduous', 'palm_trees', 'tree', 'trees']`
- Or create a group called `group_structure` and add the following features: `['barn', 'bridge', 'building', 'cabin', 'dock', 'farm', 'fence', 'lighthouse', 'mill', 'structure', 'windmill']`

Grouping these features will allow me to see the bigger picture of how different features are used together.

- We'll create multiple lists, each a different category containing the related features.

```
# Group related features, such as trees, structures, water, etc.
group_tree = ['conifer', 'deciduous', 'palm_trees', 'tree', 'trees']
group_structure = ['barn', 'bridge', 'building', 'cabin', 'dock', 'farm', 'fence', 'lighthouse', 'mill', 'structure', 'windmill']
group_water = ['beach', 'lake', 'lakes', 'ocean', 'river', 'waterfall', 'waves']
group_frame = [col for col in lowered_df.columns if 'frame' in col]
group_cloud = ['cirrus', 'clouds', 'cumulus']
group_plant = ['bushes', 'cactus', 'flowers', 'grass']
group_mountain = ['cliff', 'mountain', 'mountains', 'hills', 'snowy_mountain']
```

```
group_guest = ['diane_andre', 'guest', 'steve_ross']
group_winter = ['winter', 'snow']

all_groups = group_tree + group_structure + group_water + group_frame + group_cloud + group_plant + group_mountain + group_guest + (
```

- Then we'll add all the lists into one list named `all_groups` , create the `group_FEATURE` column in the dataframe, and finally drop the individual feature columns from the dataframe in favor of the grouped ones.
  - NOTE: We're using the `.agg()` function again with the `max` function. This is the same as saying `group_cloud = any(['cirrus', 'clouds', 'cumulus'])` for each episode. If any of those 3 features == 1, then `group_cloud` will also == 1.

```
all_groups_df = lowered_df.copy()
groups = [
    ('group_tree', group_tree), ('group_structure', group_structure),
    ('group_water', group_water), ('group_frame', group_frame),
    ('group_cloud', group_cloud), ('group_plant', group_plant),
    ('group_mountain', group_mountain), ('group_guest', group_guest),
    ('group_winter', group_winter)
]
for group_name, group_columns in sorted(groups):
    all_groups_df[group_name] = all_groups_df[group_columns].agg(func=max, axis=1)
    all_groups_df = all_groups_df.drop(labels=group_columns, axis=1)
```

Our dataframe is now much less cluttered and contains 2/3 fewer columns. We could further group the smaller features together, but I omitted this step because I wanted to show how the less-frequent features related to one another.

```
all_groups_df

--- Output ---
episode title aurora_borealis boat  fire  fog moon  night path  person  ... sun group_cloud group_frame group_guest group_mountain  grou
0 S01E01  "A WALK IN THE WOODS" 0 0 0 0 0 0 0 0 ... 0 0 0 0 0 1 0 1 1 0
1 S01E02  "MT. MCKINLEY"  0 0 0 0 0 0 0 0 ... 0 1 0 0 1 0 1 1 0 1
2 S01E03  "EBONY SUNSET"  0 0 0 0 0 0 0 0 ... 1 0 0 0 1 0 1 1 0 1
3 S01E04  "WINTER MIST" 0 0 0 0 0 0 0 0 ... 0 1 0 0 1 1 0 1 1 0
4 S01E05  "QUIET STREAM"  0 0 0 0 0 0 0 0 ... 0 0 0 0 0 0 0 1 1 0
... ... ... ... ... ... ... ... ... ... ... ... ... ... ... ... ... ... ... ... ... ... ...
398 S31E09  "EVERGREEN VALLEY"  0 0 0 0 0 0 0 0 ... 0 0 0 0 1 1 0 1 0 0
399 S31E10  "BALMY BEACH" 0 0 0 0 0 0 0 0 ... 0 0 1 0 0 0 0 1 1 0
400 S31E11  "LAKE AT THE RIDGE" 0 0 0 0 0 0 0 0 ... 0 1 0 1 1 1 0 1 1 0
401 S31E12  "IN THE MIDST OF WINTER"  0 0 0 1 0 0 1 0 ... 0 0 0 0 0 0 1 1 0 1
402 S31E13  "WILDERNESS DAY"  0 0 0 0 0 0 0 0 ... 0 0 0 0 1 1 0 1 0 0
403 rows × 22 columns
```

Frequency of Grouped Features

Let's count the appearances of all features now, including groups:

```
# Count appearances of all groups
summed_groups_df = all_groups_df.copy()
summed_groups_df = summed_groups_df.transpose().drop(labels=['episode','title'])
summed_groups = summed_groups_df.sum(axis=1).astype(int).sort_values(ascending=False)
summed_groups

--- Output ---
group_tree         369
group_water        303
group_plant        230
group_mountain     183
group_cloud        182
group_structure    102
rocks               77
snow                75
winter              69
group_frame         54
path                49
sun                 40
fog                 23
```

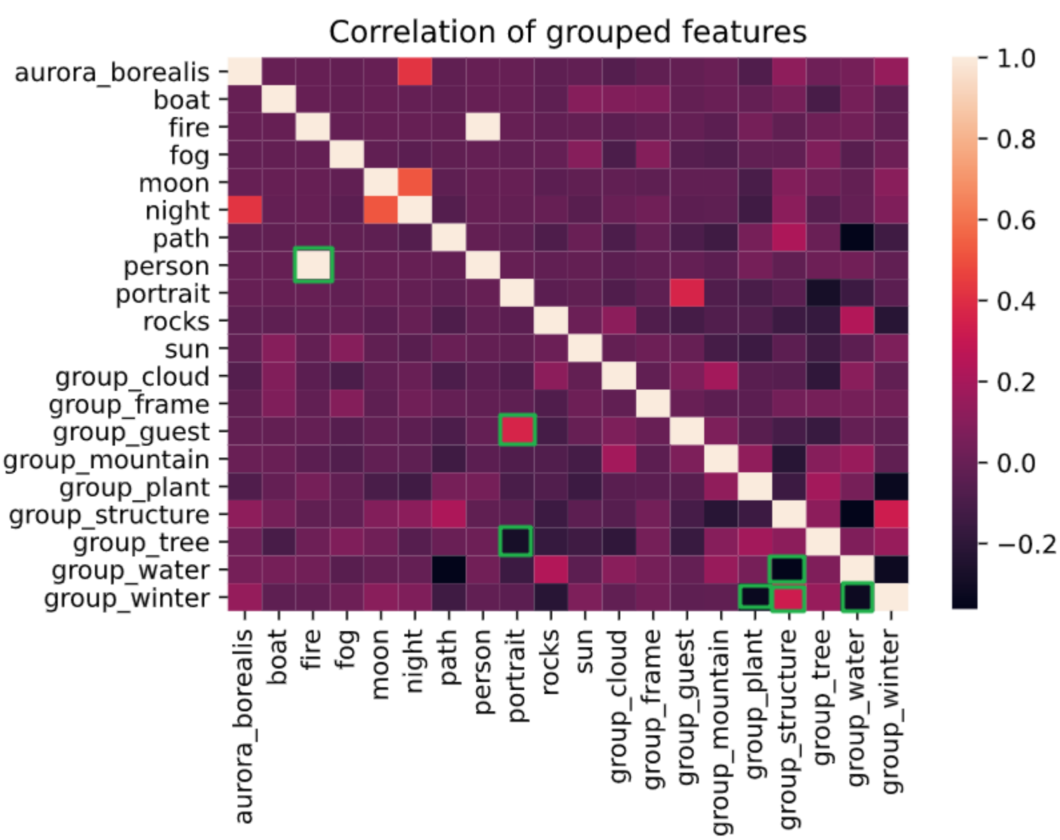
```
group_guest         22
night               11
portrait             3
moon                 3
boat                 2
aurora_borealis      2
person               1
fire                 1
dtype: int32
```

As expected, Bob Ross loved his trees. Over 91% of his paintings contained a tree! But now we also see that he frequently painted water.

Grouped Feature Correlation: Heatmap

Just like before, we can create a simple correlation heatmap and get a more generalized output now that we have groups

```
all_groups_corr = all_groups_df.corr()
ax = plt.axes()
ax.set(title='Correlation of grouped features')
sns.heatmap(all_groups_corr, yticklabels=True)  # Show every y-axis label instead of every other label
```



Interesting correlations were highlighted in green boxes

Key Findings and Insights

Feature Correlation: Insights

In order to find out which features are highly correlated, we need to refer back to the EDA lab, specifically Question#9 when we were reshaping the data.

- First we must stack the data. This will change the columns into individual rows. So, instead of have 1 row with 67 columns, we'll have a multi-indexed row with 67 sub-rows with 1 column (correlation %).

```
corr_high = corr.stack()
corr_high

--- Output ---
apple_frame  apple_frame        1.000000
             aurora_borealis   -0.003522
             barn              -0.010467
             beach             -0.013365
             boat              -0.003522
                                  ...
wood_framed  waves             -0.015140
             windmill          -0.002488
             window_frame      -0.002488
             winter            -0.022669
             wood_framed        1.000000
Length: 4356, dtype: float64
```

- Then we'll reset the index, and rename the columns, so we'll have three columns (feature1, feature2, correlation%) and one row for each correlation

```
corr_high = corr.stack().reset_index().rename(
    columns={'level_0': 'feature1', 'level_1': 'feature2', 0: 'high_corr'}
)
corr_high

--- Output ---

feature1  feature2  high_corr
0 apple_frame apple_frame 1.000000
1 apple_frame aurora_borealis -0.003522
2 apple_frame barn  -0.010467
3 apple_frame beach -0.013365
4 apple_frame boat  -0.003522
... ... ... ...
4351  wood_framed waves -0.015140
4352  wood_framed windmill  -0.002488
4353  wood_framed window_frame  -0.002488
4354  wood_framed winter  -0.022669
4355  wood_framed wood_framed 1.000000
4356 rows × 3 columns
```

- Now that we have all of the correlation values, let's filter the higher correlations and then sort them
    - Remember that correlations can be from -1.0 → 1.0. If the absolute value of the correlation == 1.0, then the feature is likely correlating with itself, so we'll have to remove that

```
corr_high = corr_high[corr_high['high_corr'].abs().between(left=0.5, right=0.99)]
corr_high = corr_high.sort_values(by='high_corr', ascending=False)
# Remove duplicates, every 2nd row is the same as the row above it except feature1/feature2 are swapped
corr_high.iloc[::2, :]

--- Output ---

      feature1    feature2          high_corr
2635  ocean       waves             0.969188
3364  snow        winter            0.916661
237   beach       ocean             0.855598
4029  waves       beach             0.847090
2666  oval_frame  framed            0.829166
3885  trees       tree              0.770751
2427  mountain    snowy_mountain    0.750383
3572  structure   cabin             0.733814
1192  dock        boat              0.706227
3526  steve_ross  guest             0.697115
2478  mountains   mountain          0.691492
```

```
1003  cumulus     clouds               0.546095
2543  night       moon                 0.516984
4084  waves       trees               -0.565289
256   beach       trees               -0.578704
2632  ocean       trees               -0.590175
4083  waves       tree                -0.685392
255   beach       tree                -0.688180
3801  tree        ocean               -0.718906
```

```
# More information on `corr_high[corr_high['high_corr'].abs().between(left=0.5, right=0.99)]`

corr_high[corr_high['high_corr'].abs().between(left=0.5, right=0.99)]
# This applies the `abs()` function to the `high_corr` column, so it turns all negative numbers into positive
# `.between(0.5, 0.99)` returns all values between 0.5 and 0.99
```

From the correlation data, we can gather the following **obvious insights**:

1. When Oceans are painted, there's a positive correlation of Waves also being painted. Make sense.
2. When a Beach is painted, there's a positive correlation of an Ocean also being painted. This also makes sense.

We can also gather the following interesting insights:

1. When a painting is Framed, it's likely it'll be an Oval Frame.
2. When a painting contains Waves, such as an Ocean or Beach painting, it's unlikely for there to be any Trees.

Grouped Feature Correlation: Insights

Grouping features has its benefits and drawbacks. In short, correlations become more muddled and vague, but you can see a bigger picture of how all related features (groups) are correlated with other groups.

- Benefits: We can develop a better understanding of the bigger picture of how features are correlated.
- Drawbacks: We lose the feature-specific correlations, such as the positive correlation of Beach/Ocean/Waves features, when features are grouped together.

From the Grouped Feature Correlation Heatmap, we can find a few interesting correlations surrounded with green boxes...

1. Person has a nearly 1.0 correlation with fire. Does Bob Ross like to pain people on fire?
2. Portraits are (highly) positively correlated with group_guests and negatively correlated with group_trees.
3. Structures are negatively correlated when the painting has water-related features, but positively correlated when the painting has winter-related features.
4. Furthermore, plant and water-related features are negatively correlated to winter-related features.

Interesting stuff, huh?

Feature Frequency: Mean and Median

We can find the Mean and Median for ungrouped and grouped features in the following code block:

- For ungrouped features, the Mean occurrence is 48 and the Median is 11.
  - It's important to remember that this data is heavily right-skewed because Mr. Ross loved to paint trees. Over 369 of the 403 paintings (92%) contained trees!
- For grouped features, the Mean occurrence is 87 and the Median is 45.
  - Grouping the features corrected the skewage a little bit... but the Happy Little Trees are eternally dominant in "The Joy of Painting".

We'll use these Mean and Median values later during our Hypothesis testing.

```
mean_df = lowered_df.copy()
mean_df.set_index(keys='episode', inplace=True)
mean_df.drop(labels='title', inplace=True, axis=1)
# Average number of occurences for each feature == 48.07
average_occur_mean = mean_df.sum().mean()
# Median number of occurences for each feature == 11
average_occur_median = mean_df.sum().median()
# The Mean (48) is skewed beause Bob Ross loves to draw trees, so we're using the Median (11) number of occurrences instead

grouped_mean_df = all_groups_df.copy()
grouped_mean_df.set_index(keys='episode', inplace=True)
grouped_mean_df.drop(labels='title', inplace=True, axis=1)
# Average number of occurences for each grouped feature == 87
average_occur_mean = grouped_mean_df.sum().mean()
# Median number of occurences for each grouped feature == 45
average_occur_median = grouped_mean_df.sum().median()
```

Formulate at least 3 hypothesis about this data

Hypothesis 1: If I choose a painting with a Mountain, it's unlikely to also have Snow

```
# Hypothesis 1: If I choose a painting with a Mountain, it's statistically more likely to also have Snow
grouped_df = lowered_df.copy()
grouped_df['group_mountain'] = grouped_df[group_mountain].agg(func=max, axis=1)
grouped_df = grouped_df.drop(labels=group_mountain, axis=1)

num_mountain_paintings = grouped_df['group_mountain'].sum()  # 183 paintings (45.41%) have a Mountain, above mean and median
grouped_df['snow'].sum()  # 75 paintings (18.61%) have Snow, above mean and median (below grouped mean)
grouped_df['snow_with_mountains'] = grouped_df['group_mountain'] & grouped_df['snow']
num_snow_and_mountain = grouped_df['snow_with_mountains'].sum()  # 31 paintings have Snow and Mountains, below the mean (48) but above the 

num_snow_and_mountain / num_mountain_paintings # 16.94% of paintings with Mountains also have Snow
```

- Result: This hypothesis was **correct!**
- In fact, the data shows that only about 17% of all Mountain paintings also contain Snow, whereas only 41% of all Snow paintings also contain a Mountain.
- Furthermore, we can see that the number of paintings that contain a Mountain (183) well exceed the Mean and Median for both ungrouped (48, 11) and grouped (87, 45) feature occurrences.

Hypothesis 2: If the painting is Framed, it's highly likely the painting will not contain a Tree

```
# Hypothesis 2: If the painting is Framed, it's highly likely the painting will not contain a Tree
grouped_df = lowered_df.copy()
grouped_df['group_tree'] = grouped_df[group_tree].agg(func=max, axis=1)
grouped_df['group_frame'] = grouped_df[group_frames].agg(func=max, axis=1)
grouped_df = grouped_df.drop(labels=group_tree+group_frames, axis=1)

num_all_paintings = len(grouped_df)                         # 403 paintings total
num_framed_paintings = grouped_df['group_frame'].sum()   # 54 Framed paintings
num_framed_paintings / num_all_paintings                 # 13.39% of paintings are Framed

grouped_df['tree_and_frame'] = grouped_df['group_tree'] & grouped_df['group_frame']
num_tree_and_frame = grouped_df['tree_and_frame'].sum()  # 51 Framed paintings with trees
```

```
num_tree_and_frame / num_all_paintings                      # 12.66% of paintings are Framed with Trees
num_tree_and_frame / num_framed_paintings                   # 94.44% of Framed paintings have Trees
```

- Result: This hypothesis was **incorrect!**
- It turns out that 94% of framed paintings also contain a tree. This is unsurprising after discovering over 91% of Bob's paintings contain a tree.
- No need to compare against the Mean and Median value here.

Hypothesis 3: If it's a Winter painting, Bob Ross will have also painted a Structure

```
# Hypothesis 3: If it's a Winter painting, Bob Ross will have also painted a Structure
# Short and neat way to create the same winter_and_structure column as below
all_groups_df[all_groups_df['group_winter'] == 1].loc[    # Bob Ross has 77 Winter paintings (above the mean & median), 19.10% of all painti
    all_groups_df['group_structure'] == 1].loc[          # of the 77 Winter paintings, 41 contain a Structure (above median) (53.24%)
        all_groups_df['group_guest'] == 0]               # 22 episodes with guests, 5.45% (22/403) of all episodes are guests

grouped_df = lowered_df.copy()
grouped_df['group_winter'] = grouped_df[group_winter].agg(func=max, axis=1)
grouped_df['group_structure'] = grouped_df[group_structure].agg(func=max, axis=1)
grouped_df['group_guest'] = grouped_df[group_guest].agg(func=max, axis=1)

grouped_df = grouped_df.drop(labels=group_winter+group_structure, axis=1)
num_all_paintings = len(grouped_df)
num_winter_paintings = grouped_df['group_winter'].sum()           # 77 Winter paintings
num_structure_paintings = grouped_df['group_structure'].sum()     # 102 paintings with a Structure

num_winter_paintings / num_all_paintings                          # 19.10% of all paintings are Winter-related
num_structure_paintings / num_all_paintings                       # 25.31% of all paintings have a structure

grouped_df['winter_and_structure'] = grouped_df['group_winter'] & grouped_df['group_structure']
# Make sure it's by Bob Ross, not a Guest
grouped_df['winter_and_structure'] = grouped_df['winter_and_structure'].loc[grouped_df['group_guest'] == 0]
num_winter_and_structure = grouped_df['winter_and_structure'].sum()  # 41 Winter paintings by Bob Ross with a Structure
num_winter_and_structure / num_all_paintings                         # 10.42% of paintings are Winter with Structure
num_winter_and_structure / num_winter_paintings                      # 53.25% of Winter paintings have a Structure
```

- Result: This hypothesis is pointing slightly towards correct, but it's too close to tell.
- There are 41 Winter paintings that contain a Structure.
    - This number is lower than the ungrouped Mean of 48 and grouped Mean and Median of (87, 45), so it's unlikely you'll select a Winter painting that also contains a Structure.
        - BUT, if you're watching Bob Ross paint a Winter scene, there's a little over 50% chance that he'll also paint a Structure.
    - 41 Winter paintings with a Structure is higher than the ungrouped Median of 11. However, I am using grouped features in this hypothesis so it does not make sense to compare the grouped values against ungrouped values.

Conducting a formal significance test for one of the hypotheses and discuss the results

Unfortunately, because the dataset is categorical, we are unable to do a true formal significance test.

- This is an oversight on my part. After selecting the dataset, and formulating my hypotheses, I was unaware that you could not normalize skewed categorical data.
- So, instead of performing a significance test, I compared all hypotheses to the Mean and Median values for both ungrouped and grouped features.

Suggestions for next steps in analyzing this data

The next steps in analyzing this data could include describing how Bob Ross & friends name their paintings based on what features were included. Often, the main feature would also have a keyword in the title.

- For example, if the painting had a lake, it would often include the word "Lake" in the title.

One could analyze how much weight each feature had on the naming scheme of the painting's final title.

Data Set Summary

The data was categorical, simple, and easy to work with and understand at first glance.

However, after deep diving into some of the features and watching the related "The Joy of Painting" episodes, I noticed a few discrepancies in the features. For example in S03E04, the painting's title is "Winter Night", but the winter label is 0, whereas the snow label is 1.

This led me to question how the dataset's author decided whether a painting included a feature or not. However, it's important to note that discrepancies of this nature are easily resolved by grouping related features.