01_EXPLORE - Galaxy morphology dataset

Date: 07-09-2025

Goals: Inspect galaxy zoo 2 dataset, show label distribution, sample images and captions, quality check, and verify for leakage before training.

In [32]:
```
# imports
import os
import random
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from PIL import Image
from IPython.display import display
from pathlib import Path

sns.set(style='whitegrid')

random.seed(5629)
np.random.seed(5629)
try:
    PROJECT_ROOT = Path(__file__).resolve().parents[2]
except NameError:
    PROJECT_ROOT = Path.cwd().resolve().parent
DATA_PATH = PROJECT_ROOT / "data" / "labels"
labels_filepath = DATA_PATH / "labels_manifest_1000.csv"
thumbnails_directory = DATA_PATH / "thumbs"

manifest_labels_fp = PROJECT_ROOT / "data" / "processed" / "manifest_with_labels.cs
```

This section presents the inspection of the dataset for issues, as well as exploration of its structure and contents of it.

Let's start by getting familiar with the data. Here is a list of all the columns:

In [33]:
```
df = pd.read_csv(labels_filepath)
dfm = pd.read_csv(manifest_labels_fp)
print("Rows in full dataset: \n", dfm.shape[0])
print("Columns in full dataset: \n", dfm.columns.tolist())
print("Rows in sample: \n", df.shape[0])
print("Columns in sample: \n", df.columns.tolist())
print("Manifest head:\n")
dfm.head()
```

```
Rows in full dataset:
 239572
Columns in full dataset:
 ['objid', 'sample', 'asset_id', 'dr7objid', 'gz2_class', 'total_classifications', '
total_votes', 't01_smooth_or_features_a01_smooth_fraction', 't01_smooth_or_features_
a01_smooth_weighted_fraction', 't01_smooth_or_features_a01_smooth_debiased', 't01_sm
ooth_or_features_a02_features_or_disk_fraction', 't01_smooth_or_features_a02_feature
s_or_disk_weighted_fraction', 't01_smooth_or_features_a02_features_or_disk_debiased'
, 't01_smooth_or_features_a03_star_or_artifact_weighted_fraction', 't01_smooth_or_fe
atures_a03_star_or_artifact_debiased', 't02_edgeon_a04_yes_weighted_fraction', 't02_
edgeon_a04_yes_debiased', 't02_edgeon_a05_no_weighted_fraction', 't02_edgeon_a05_no_
debiased', 't03_bar_a06_bar_weighted_fraction', 't03_bar_a06_bar_debiased', 't03_bar
_a07_no_bar_weighted_fraction', 't03_bar_a07_no_bar_debiased', 't04_spiral_a08_spira
l_weighted_fraction', 't04_spiral_a08_spiral_debiased', 't04_spiral_a09_no_spiral_we
ighted_fraction', 't04_spiral_a09_no_spiral_debiased', 't05_bulge_prominence_a10_no_
bulge_weighted_fraction', 't05_bulge_prominence_a10_no_bulge_debiased', 't05_bulge_p
rominence_a11_just_noticeable_weighted_fraction', 't05_bulge_prominence_a11_just_not
iceable_debiased', 't05_bulge_prominence_a12_obvious_weighted_fraction', 't05_bulge_
prominence_a12_obvious_debiased', 't05_bulge_prominence_a13_dominant_weighted_fracti
on', 't05_bulge_prominence_a13_dominant_debiased', 't06_odd_a14_yes_weighted_fractio
n', 't06_odd_a14_yes_debiased', 't06_odd_a15_no_weighted_fraction', 't06_odd_a15_no_
debiased', 't07_rounded_a16_completely_round_weighted_fraction', 't07_rounded_a16_co
mpletely_round_debiased', 't07_rounded_a17_in_between_weighted_fraction', 't07_round
ed_a17_in_between_debiased', 't07_rounded_a18_cigar_shaped_weighted_fraction', 't07_
rounded_a18_cigar_shaped_debiased', 't08_odd_feature_a19_ring_weighted_fraction', 't
08_odd_feature_a19_ring_debiased', 't08_odd_feature_a20_lens_or_arc_weighted_fractio
n', 't08_odd_feature_a20_lens_or_arc_debiased', 't08_odd_feature_a21_disturbed_weigh
ted_fraction', 't08_odd_feature_a21_disturbed_debiased', 't08_odd_feature_a22_irregu
lar_weighted_fraction', 't08_odd_feature_a22_irregular_debiased', 't08_odd_feature_a
23_other_weighted_fraction', 't08_odd_feature_a23_other_debiased', 't08_odd_feature_
a24_merger_weighted_fraction', 't08_odd_feature_a24_merger_debiased', 't08_odd_featu
re_a38_dust_lane_weighted_fraction', 't08_odd_feature_a38_dust_lane_debiased', 't09_
bulge_shape_a25_rounded_weighted_fraction', 't09_bulge_shape_a25_rounded_debiased',
 't09_bulge_shape_a26_boxy_weighted_fraction', 't09_bulge_shape_a26_boxy_debiased', '
t09_bulge_shape_a27_no_bulge_weighted_fraction', 't09_bulge_shape_a27_no_bulge_debia
sed', 't10_arms_winding_a28_tight_weighted_fraction', 't10_arms_winding_a28_tight_de
biased', 't10_arms_winding_a29_medium_weighted_fraction', 't10_arms_winding_a29_medi
um_debiased', 't10_arms_winding_a30_loose_weighted_fraction', 't10_arms_winding_a30_
loose_debiased', 't11_arms_number_a31_1_weighted_fraction', 't11_arms_number_a31_1_d
ebiased', 't11_arms_number_a32_2_weighted_fraction', 't11_arms_number_a32_2_debiased
', 't11_arms_number_a33_3_weighted_fraction', 't11_arms_number_a33_3_debiased', 't11
_arms_number_a34_4_weighted_fraction', 't11_arms_number_a34_4_debiased', 't11_arms_n
umber_a36_more_than_4_weighted_fraction', 't11_arms_number_a36_more_than_4_debiased'
, 't11_arms_number_a37_cant_tell_weighted_fraction', 't11_arms_number_a37_cant_tell_
debiased', 'asset_key', 'objid_key', 'score_spiral', 'score_smooth', 'score_edge', '
score_merger', 'score_bar', 'derived_label', 'filepath']
Rows in sample:
 1000
Columns in sample:
 ['objid', 'sample', 'asset_id', 'dr7objid', 'gz2_class', 'total_classifications', '
total_votes', 't01_smooth_or_features_a01_smooth_fraction', 't01_smooth_or_features_
a01_smooth_weighted_fraction', 't01_smooth_or_features_a01_smooth_debiased', 't01_sm
ooth_or_features_a02_features_or_disk_fraction', 't01_smooth_or_features_a02_feature
s_or_disk_weighted_fraction', 't01_smooth_or_features_a02_features_or_disk_debiased'
, 't01_smooth_or_features_a03_star_or_artifact_weighted_fraction', 't01_smooth_or_fe
atures_a03_star_or_artifact_debiased', 't02_edgeon_a04_yes_weighted_fraction', 't02_
```

```
edgeon_a04_yes_debiased', 't02_edgeon_a05_no_weighted_fraction', 't02_edgeon_a05_no_
debiased', 't03_bar_a06_bar_weighted_fraction', 't03_bar_a06_bar_debiased', 't03_bar
_a07_no_bar_weighted_fraction', 't03_bar_a07_no_bar_debiased', 't04_spiral_a08_spira
l_weighted_fraction', 't04_spiral_a08_spiral_debiased', 't04_spiral_a09_no_spiral_we
ighted_fraction', 't04_spiral_a09_no_spiral_debiased', 't05_bulge_prominence_a10_no_
bulge_weighted_fraction', 't05_bulge_prominence_a10_no_bulge_debiased', 't05_bulge_p
rominence_a11_just_noticeable_weighted_fraction', 't05_bulge_prominence_a11_just_not
iceable_debiased', 't05_bulge_prominence_a12_obvious_weighted_fraction', 't05_bulge_
prominence_a12_obvious_debiased', 't05_bulge_prominence_a13_dominant_weighted_fracti
on', 't05_bulge_prominence_a13_dominant_debiased', 't06_odd_a14_yes_weighted_fractio
n', 't06_odd_a14_yes_debiased', 't06_odd_a15_no_weighted_fraction', 't06_odd_a15_no_
debiased', 't07_rounded_a16_completely_round_weighted_fraction', 't07_rounded_a16_co
mpletely_round_debiased', 't07_rounded_a17_in_between_weighted_fraction', 't07_round
ed_a17_in_between_debiased', 't07_rounded_a18_cigar_shaped_weighted_fraction', 't07_
rounded_a18_cigar_shaped_debiased', 't08_odd_feature_a19_ring_weighted_fraction', 't
08_odd_feature_a19_ring_debiased', 't08_odd_feature_a20_lens_or_arc_weighted_fractio
n', 't08_odd_feature_a20_lens_or_arc_debiased', 't08_odd_feature_a21_disturbed_weigh
ted_fraction', 't08_odd_feature_a21_disturbed_debiased', 't08_odd_feature_a22_irregu
lar_weighted_fraction', 't08_odd_feature_a22_irregular_debiased', 't08_odd_feature_a
23_other_weighted_fraction', 't08_odd_feature_a23_other_debiased', 't08_odd_feature_
a24_merger_weighted_fraction', 't08_odd_feature_a24_merger_debiased', 't08_odd_featu
re_a38_dust_lane_weighted_fraction', 't08_odd_feature_a38_dust_lane_debiased', 't09_
bulge_shape_a25_rounded_weighted_fraction', 't09_bulge_shape_a25_rounded_debiased',
 't09_bulge_shape_a26_boxy_weighted_fraction', 't09_bulge_shape_a26_boxy_debiased', '
t09_bulge_shape_a27_no_bulge_weighted_fraction', 't09_bulge_shape_a27_no_bulge_debia
sed', 't10_arms_winding_a28_tight_weighted_fraction', 't10_arms_winding_a28_tight_de
biased', 't10_arms_winding_a29_medium_weighted_fraction', 't10_arms_winding_a29_medi
um_debiased', 't10_arms_winding_a30_loose_weighted_fraction', 't10_arms_winding_a30_
loose_debiased', 't11_arms_number_a31_1_weighted_fraction', 't11_arms_number_a31_1_d
ebiased', 't11_arms_number_a32_2_weighted_fraction', 't11_arms_number_a32_2_debiased
', 't11_arms_number_a33_3_weighted_fraction', 't11_arms_number_a33_3_debiased', 't11
_arms_number_a34_4_weighted_fraction', 't11_arms_number_a34_4_debiased', 't11_arms_n
umber_a36_more_than_4_weighted_fraction', 't11_arms_number_a36_more_than_4_debiased'
, 't11_arms_number_a37_cant_tell_weighted_fraction', 't11_arms_number_a37_cant_tell_
debiased', 'asset_key', 'objid_key', 'score_spiral', 'score_smooth', 'score_edge', '
score_merger', 'score_bar', 'derived_label', 'filepath']
Manifest head:
```

Out[33]:

	objid	sample	asset_id	dr7objid	gz2_class	total_classificatio
0	587722981741363294	original	3	587722981741363294	Sb	52
1	587722981741363323	original	4	587722981741363323	Sc?l	30
2	587722981741559888	original	5	587722981741559888	Er	53
3	587722981741625481	original	6	587722981741625481	Sc1t	37
4	587722981741625484	original	7	587722981741625484	Sb	45

5 rows × 92 columns

In [34]:
```python
print("Sample head:\n")
df.head()
```

```
Sample head:
```

Out[34]:

	objid	sample	asset_id	dr7objid	gz2_class	total_classificatio
0	587739505552785605	original	130549	587739505552785605	Sc?t	38
1	587732578312454276	original	57314	587732578312454276	SBc4t	38
2	587729154670395609	original	29846	587729154670395609	Sb?m	39
3	587732154179452963	original	52897	587732154179452963	SBb2m	30
4	587722983364690145	original	1129	587722983364690145	Sc?m	35

5 rows × 92 columns

Both the manifest and the sample contain **93** columns. Every object's id (**objid**), sample from which it was taken (original or extra), a couple more ids, the class of the object using the galaxy zoo classification, the total votes that the object received, and a long list of features: criteria that people were voting upon, and the fraction of the voters that recognized every given feature in the image. In the end, are the calculated scores for every class: **score_spiral, smooth, edge, merger and bar**. It is a number between 0 and 1 representing how prominent every feature is. The derived_label column then combines all the features using logic to determine the label of the image: **spiral**, **elliptical**, **edge-on**, **merger** or **ambiguous** if a consensus was not met within the voters. **Filepath** is, well, the filepath (from project root [before that I worked with hardcoded windows paths, but dropped them for reproducibility reasons]).

In [35]:
```python
print("FULL DATASET:\n")
print("Basic information about the columns:\n")
display(dfm.info())
print("\nAmount of missing values in each column:\n")
display(dfm.isna().sum().sort_values(ascending=False))

print("\nSAMPLE:\n")
print("Basic information about the columns:\n")
display(df.info())
print("\nAmount of missing values in each column:\n")
display(df.isna().sum().sort_values(ascending=False))
```

```
FULL DATASET:

Basic information about the columns:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 239572 entries, 0 to 239571
Data columns (total 92 columns):
 #   Column                                                    Non-Null Count
Dtype
---  ------                                                    --------------
-----
 0   objid                                                     239572 non-null
int64
 1   sample                                                    239572 non-null
object
 2   asset_id                                                  239572 non-null
int64
 3   dr7objid                                                  239572 non-null
int64
 4   gz2_class                                                 239572 non-null
object
 5   total_classifications                                     239572 non-null
float64
 6   total_votes                                               239572 non-null
float64
 7   t01_smooth_or_features_a01_smooth_fraction                239572 non-null
float64
 8   t01_smooth_or_features_a01_smooth_weighted_fraction       239572 non-null
float64
 9   t01_smooth_or_features_a01_smooth_debiased                239572 non-null
float64
 10  t01_smooth_or_features_a02_features_or_disk_fraction      239572 non-null
float64
 11  t01_smooth_or_features_a02_features_or_disk_weighted_fraction  239572 non-null
float64
 12  t01_smooth_or_features_a02_features_or_disk_debiased      239572 non-null
float64
 13  t01_smooth_or_features_a03_star_or_artifact_weighted_fraction  239572 non-null
float64
 14  t01_smooth_or_features_a03_star_or_artifact_debiased      239572 non-null
float64
 15  t02_edgeon_a04_yes_weighted_fraction                      239572 non-null
float64
 16  t02_edgeon_a04_yes_debiased                               239572 non-null
float64
 17  t02_edgeon_a05_no_weighted_fraction                       239572 non-null
float64
 18  t02_edgeon_a05_no_debiased                                239278 non-null
float64
 19  t03_bar_a06_bar_weighted_fraction                         239572 non-null
float64
 20  t03_bar_a06_bar_debiased                                  239572 non-null
float64
 21  t03_bar_a07_no_bar_weighted_fraction                      239572 non-null
float64
 22  t03_bar_a07_no_bar_debiased                               239292 non-null
```

```
float64
 23  t04_spiral_a08_spiral_weighted_fraction                         239572 non-null
float64
 24  t04_spiral_a08_spiral_debiased                                  239572 non-null
float64
 25  t04_spiral_a09_no_spiral_weighted_fraction                      239572 non-null
float64
 26  t04_spiral_a09_no_spiral_debiased                               239284 non-null
float64
 27  t05_bulge_prominence_a10_no_bulge_weighted_fraction             239572 non-null
float64
 28  t05_bulge_prominence_a10_no_bulge_debiased                      239572 non-null
float64
 29  t05_bulge_prominence_a11_just_noticeable_weighted_fraction      239572 non-null
float64
 30  t05_bulge_prominence_a11_just_noticeable_debiased               239572 non-null
float64
 31  t05_bulge_prominence_a12_obvious_weighted_fraction              239572 non-null
float64
 32  t05_bulge_prominence_a12_obvious_debiased                       239572 non-null
float64
 33  t05_bulge_prominence_a13_dominant_weighted_fraction             239572 non-null
float64
 34  t05_bulge_prominence_a13_dominant_debiased                      239369 non-null
float64
 35  t06_odd_a14_yes_weighted_fraction                               239572 non-null
float64
 36  t06_odd_a14_yes_debiased                                        239296 non-null
float64
 37  t06_odd_a15_no_weighted_fraction                                239572 non-null
float64
 38  t06_odd_a15_no_debiased                                         239572 non-null
float64
 39  t07_rounded_a16_completely_round_weighted_fraction              239572 non-null
float64
 40  t07_rounded_a16_completely_round_debiased                       239332 non-null
float64
 41  t07_rounded_a17_in_between_weighted_fraction                    239572 non-null
float64
 42  t07_rounded_a17_in_between_debiased                             239572 non-null
float64
 43  t07_rounded_a18_cigar_shaped_weighted_fraction                  239572 non-null
float64
 44  t07_rounded_a18_cigar_shaped_debiased                           239572 non-null
float64
 45  t08_odd_feature_a19_ring_weighted_fraction                      239572 non-null
float64
 46  t08_odd_feature_a19_ring_debiased                               239572 non-null
float64
 47  t08_odd_feature_a20_lens_or_arc_weighted_fraction               239572 non-null
float64
 48  t08_odd_feature_a20_lens_or_arc_debiased                        239572 non-null
float64
 49  t08_odd_feature_a21_disturbed_weighted_fraction                 239572 non-null
float64
 50  t08_odd_feature_a21_disturbed_debiased                          239572 non-null
```

```
float64
 51  t08_odd_feature_a22_irregular_weighted_fraction              239572 non-null
float64
 52  t08_odd_feature_a22_irregular_debiased                       239572 non-null
float64
 53  t08_odd_feature_a23_other_weighted_fraction                  239572 non-null
float64
 54  t08_odd_feature_a23_other_debiased                           239572 non-null
float64
 55  t08_odd_feature_a24_merger_weighted_fraction                 239572 non-null
float64
 56  t08_odd_feature_a24_merger_debiased                          239572 non-null
float64
 57  t08_odd_feature_a38_dust_lane_weighted_fraction              239572 non-null
float64
 58  t08_odd_feature_a38_dust_lane_debiased                       239561 non-null
float64
 59  t09_bulge_shape_a25_rounded_weighted_fraction                239572 non-null
float64
 60  t09_bulge_shape_a25_rounded_debiased                         239472 non-null
float64
 61  t09_bulge_shape_a26_boxy_weighted_fraction                   239572 non-null
float64
 62  t09_bulge_shape_a26_boxy_debiased                            239532 non-null
float64
 63  t09_bulge_shape_a27_no_bulge_weighted_fraction               239572 non-null
float64
 64  t09_bulge_shape_a27_no_bulge_debiased                        239572 non-null
float64
 65  t10_arms_winding_a28_tight_weighted_fraction                 239572 non-null
float64
 66  t10_arms_winding_a28_tight_debiased                          239572 non-null
float64
 67  t10_arms_winding_a29_medium_weighted_fraction                239572 non-null
float64
 68  t10_arms_winding_a29_medium_debiased                         239572 non-null
float64
 69  t10_arms_winding_a30_loose_weighted_fraction                 239572 non-null
float64
 70  t10_arms_winding_a30_loose_debiased                          239572 non-null
float64
 71  t11_arms_number_a31_1_weighted_fraction                      239572 non-null
float64
 72  t11_arms_number_a31_1_debiased                               239566 non-null
float64
 73  t11_arms_number_a32_2_weighted_fraction                      239572 non-null
float64
 74  t11_arms_number_a32_2_debiased                               239552 non-null
float64
 75  t11_arms_number_a33_3_weighted_fraction                      239572 non-null
float64
 76  t11_arms_number_a33_3_debiased                               239572 non-null
float64
 77  t11_arms_number_a34_4_weighted_fraction                      239572 non-null
float64
 78  t11_arms_number_a34_4_debiased                               239572 non-null
```

```
float64
 79  t11_arms_number_a36_more_than_4_weighted_fraction              239572 non-null
float64
 80  t11_arms_number_a36_more_than_4_debiased                       239572 non-null
float64
 81  t11_arms_number_a37_cant_tell_weighted_fraction                239572 non-null
float64
 82  t11_arms_number_a37_cant_tell_debiased                         239572 non-null
float64
 83  asset_key                                                      239572 non-null
int64
 84  objid_key                                                      239572 non-null
int64
 85  score_spiral                                                   239572 non-null
float64
 86  score_smooth                                                   239572 non-null
float64
 87  score_edge                                                     239572 non-null
float64
 88  score_merger                                                   239572 non-null
float64
 89  score_bar                                                      239572 non-null
float64
 90  derived_label                                                  239572 non-null
object
 91  filepath                                                       239572 non-null
object
dtypes: float64(83), int64(5), object(4)
memory usage: 168.2+ MB
None
Amount of missing values in each column:

t02_edgeon_a05_no_debiased                    294
t04_spiral_a09_no_spiral_debiased             288
t03_bar_a07_no_bar_debiased                   280
t06_odd_a14_yes_debiased                      276
t07_rounded_a16_completely_round_debiased     240
                                             ...
score_edge                                      0
score_merger                                    0
score_bar                                       0
derived_label                                   0
filepath                                        0
Length: 92, dtype: int64
```

SAMPLE:

Basic information about the columns:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 92 columns):
 #   Column                                                         Non-Null Count
Dtype
---  ------                                                         --------------
-----
 0   objid                                                          1000 non-null
int64
 1   sample                                                         1000 non-null
object
 2   asset_id                                                       1000 non-null
int64
 3   dr7objid                                                       1000 non-null
int64
 4   gz2_class                                                      1000 non-null
object
 5   total_classifications                                          1000 non-null
float64
 6   total_votes                                                    1000 non-null
float64
 7   t01_smooth_or_features_a01_smooth_fraction                     1000 non-null
float64
 8   t01_smooth_or_features_a01_smooth_weighted_fraction            1000 non-null
float64
 9   t01_smooth_or_features_a01_smooth_debiased                     1000 non-null
float64
 10  t01_smooth_or_features_a02_features_or_disk_fraction           1000 non-null
float64
 11  t01_smooth_or_features_a02_features_or_disk_weighted_fraction  1000 non-null
float64
 12  t01_smooth_or_features_a02_features_or_disk_debiased           1000 non-null
float64
 13  t01_smooth_or_features_a03_star_or_artifact_weighted_fraction  1000 non-null
float64
 14  t01_smooth_or_features_a03_star_or_artifact_debiased           1000 non-null
float64
 15  t02_edgeon_a04_yes_weighted_fraction                           1000 non-null
float64
 16  t02_edgeon_a04_yes_debiased                                    1000 non-null
float64
 17  t02_edgeon_a05_no_weighted_fraction                            1000 non-null
float64
 18  t02_edgeon_a05_no_debiased                                     999 non-null
float64
 19  t03_bar_a06_bar_weighted_fraction                              1000 non-null
float64
 20  t03_bar_a06_bar_debiased                                       1000 non-null
float64
 21  t03_bar_a07_no_bar_weighted_fraction                           1000 non-null
float64
 22  t03_bar_a07_no_bar_debiased                                    999 non-null
```

```
float64
 23  t04_spiral_a08_spiral_weighted_fraction                         1000 non-null
float64
 24  t04_spiral_a08_spiral_debiased                                  1000 non-null
float64
 25  t04_spiral_a09_no_spiral_weighted_fraction                      1000 non-null
float64
 26  t04_spiral_a09_no_spiral_debiased                               999 non-null
float64
 27  t05_bulge_prominence_a10_no_bulge_weighted_fraction             1000 non-null
float64
 28  t05_bulge_prominence_a10_no_bulge_debiased                      1000 non-null
float64
 29  t05_bulge_prominence_a11_just_noticeable_weighted_fraction      1000 non-null
float64
 30  t05_bulge_prominence_a11_just_noticeable_debiased               1000 non-null
float64
 31  t05_bulge_prominence_a12_obvious_weighted_fraction              1000 non-null
float64
 32  t05_bulge_prominence_a12_obvious_debiased                       1000 non-null
float64
 33  t05_bulge_prominence_a13_dominant_weighted_fraction             1000 non-null
float64
 34  t05_bulge_prominence_a13_dominant_debiased                      1000 non-null
float64
 35  t06_odd_a14_yes_weighted_fraction                               1000 non-null
float64
 36  t06_odd_a14_yes_debiased                                        1000 non-null
float64
 37  t06_odd_a15_no_weighted_fraction                                1000 non-null
float64
 38  t06_odd_a15_no_debiased                                         1000 non-null
float64
 39  t07_rounded_a16_completely_round_weighted_fraction              1000 non-null
float64
 40  t07_rounded_a16_completely_round_debiased                       999 non-null
float64
 41  t07_rounded_a17_in_between_weighted_fraction                    1000 non-null
float64
 42  t07_rounded_a17_in_between_debiased                             1000 non-null
float64
 43  t07_rounded_a18_cigar_shaped_weighted_fraction                  1000 non-null
float64
 44  t07_rounded_a18_cigar_shaped_debiased                           1000 non-null
float64
 45  t08_odd_feature_a19_ring_weighted_fraction                      1000 non-null
float64
 46  t08_odd_feature_a19_ring_debiased                               1000 non-null
float64
 47  t08_odd_feature_a20_lens_or_arc_weighted_fraction               1000 non-null
float64
 48  t08_odd_feature_a20_lens_or_arc_debiased                        1000 non-null
float64
 49  t08_odd_feature_a21_disturbed_weighted_fraction                 1000 non-null
float64
 50  t08_odd_feature_a21_disturbed_debiased                          1000 non-null
```

```
float64
 51  t08_odd_feature_a22_irregular_weighted_fraction                   1000 non-null
float64
 52  t08_odd_feature_a22_irregular_debiased                            1000 non-null
float64
 53  t08_odd_feature_a23_other_weighted_fraction                       1000 non-null
float64
 54  t08_odd_feature_a23_other_debiased                                1000 non-null
float64
 55  t08_odd_feature_a24_merger_weighted_fraction                      1000 non-null
float64
 56  t08_odd_feature_a24_merger_debiased                               1000 non-null
float64
 57  t08_odd_feature_a38_dust_lane_weighted_fraction                   1000 non-null
float64
 58  t08_odd_feature_a38_dust_lane_debiased                            1000 non-null
float64
 59  t09_bulge_shape_a25_rounded_weighted_fraction                     1000 non-null
float64
 60  t09_bulge_shape_a25_rounded_debiased                              1000 non-null
float64
 61  t09_bulge_shape_a26_boxy_weighted_fraction                        1000 non-null
float64
 62  t09_bulge_shape_a26_boxy_debiased                                 1000 non-null
float64
 63  t09_bulge_shape_a27_no_bulge_weighted_fraction                    1000 non-null
float64
 64  t09_bulge_shape_a27_no_bulge_debiased                             1000 non-null
float64
 65  t10_arms_winding_a28_tight_weighted_fraction                      1000 non-null
float64
 66  t10_arms_winding_a28_tight_debiased                               1000 non-null
float64
 67  t10_arms_winding_a29_medium_weighted_fraction                     1000 non-null
float64
 68  t10_arms_winding_a29_medium_debiased                              1000 non-null
float64
 69  t10_arms_winding_a30_loose_weighted_fraction                      1000 non-null
float64
 70  t10_arms_winding_a30_loose_debiased                               1000 non-null
float64
 71  t11_arms_number_a31_1_weighted_fraction                           1000 non-null
float64
 72  t11_arms_number_a31_1_debiased                                    1000 non-null
float64
 73  t11_arms_number_a32_2_weighted_fraction                           1000 non-null
float64
 74  t11_arms_number_a32_2_debiased                                    1000 non-null
float64
 75  t11_arms_number_a33_3_weighted_fraction                           1000 non-null
float64
 76  t11_arms_number_a33_3_debiased                                    1000 non-null
float64
 77  t11_arms_number_a34_4_weighted_fraction                           1000 non-null
float64
 78  t11_arms_number_a34_4_debiased                                    1000 non-null
```

```
float64
 79  t11_arms_number_a36_more_than_4_weighted_fraction              1000 non-null
float64
 80  t11_arms_number_a36_more_than_4_debiased                       1000 non-null
float64
 81  t11_arms_number_a37_cant_tell_weighted_fraction                1000 non-null
float64
 82  t11_arms_number_a37_cant_tell_debiased                         1000 non-null
float64
 83  asset_key                                                      1000 non-null
int64
 84  objid_key                                                      1000 non-null
int64
 85  score_spiral                                                   1000 non-null
float64
 86  score_smooth                                                   1000 non-null
float64
 87  score_edge                                                     1000 non-null
float64
 88  score_merger                                                   1000 non-null
float64
 89  score_bar                                                      1000 non-null
float64
 90  derived_label                                                  1000 non-null
object
 91  filepath                                                       1000 non-null
object
dtypes: float64(83), int64(5), object(4)
memory usage: 718.9+ KB
None
Amount of missing values in each column:

t03_bar_a07_no_bar_debiased                 1
t04_spiral_a09_no_spiral_debiased           1
t02_edgeon_a05_no_debiased                  1
t07_rounded_a16_completely_round_debiased   1
gz2_class                                   0
                                           ..
score_edge                                  0
score_merger                                0
score_bar                                   0
derived_label                               0
filepath                                    0
Length: 92, dtype: int64
```

As can be seen, only **4** columns from **93** in the sample contain one missing value, which is not a problem, because we are going to drop them anyway. They all come from one entry: entry 476, so if I were to use the columns it would be wiser to drop that row.

However, in the full dataset there are **9** columns with missing values, ranging from 11 to 294 values missing. It contributes to ~13% of all columns, and at most 1% of the rows. Importantly, there were **122** entries missing a filepath. The easiest approach would be to entirely discard all of them.

Now, let's check all the entries to be unique (assert that there are no duplicates):

In [36]:
```
print("Unique object ids (sample):\n")
display(df.nunique())
print("\nUnique object ids (full dataset):\n")
display(dfm.nunique())
```

```
Unique object ids (sample):

objid            1000
sample              3
asset_id         1000
dr7objid         1000
gz2_class         128
                 ...
score_edge        462
score_merger      395
score_bar           1
derived_label       4
filepath         1000
Length: 92, dtype: int64
Unique object ids (full dataset):

objid            239572
sample                3
asset_id         239572
dr7objid         239572
gz2_class           818
                  ...
score_edge        95851
score_merger      70855
score_bar             1
derived_label         5
filepath         239572
Length: 92, dtype: int64
```

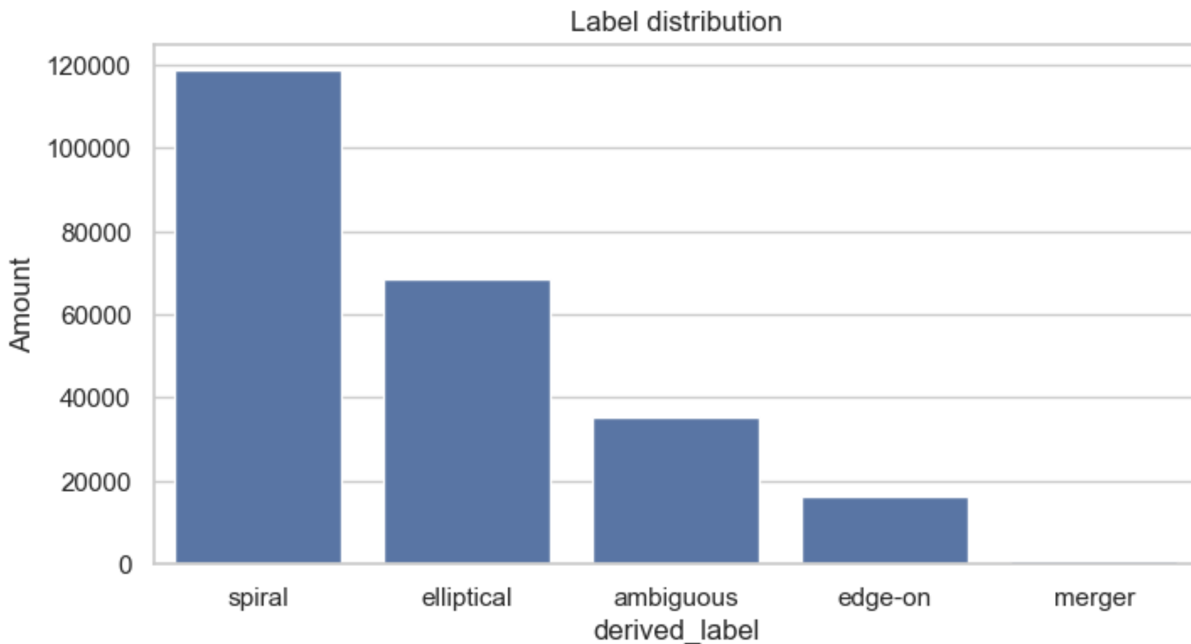
Therefore, all the ids of the dataset and the sample are unique and are ready to be used!

Let's explore the labels' distribution. After looking at the label column, it looks like most galaxies are spiral, with less elliptical ones, and edge-on were rare. Only a few were ambiguous. In the sample, we included equal parts (25% each) of all the categories, except for ambiguous. Here are all the labels and their distribution:

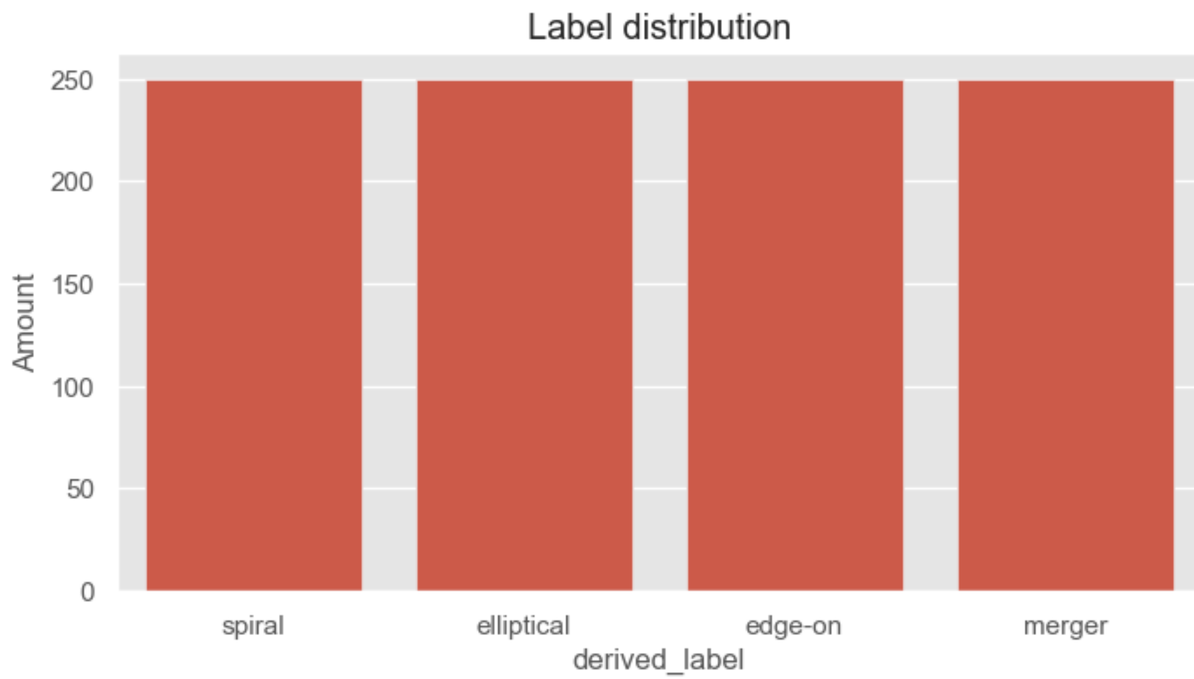
In [37]:
```
print("FULL\n")
print(dfm['derived_label'].value_counts())
plt.figure(figsize = (8,4))
sns.barplot(x=dfm['derived_label'].value_counts().index, y=dfm['derived_label'].val
plt.ylabel('Amount')
plt.title('Label distribution')
plt.style.use('ggplot')
plt.show()

print("\nSAMPLE\n")
print(df['derived_label'].value_counts())
```

```
plt.figure(figsize = (8,4))
sns.barplot(x=df['derived_label'].value_counts().index, y=df['derived_label'].value
plt.ylabel('Amount')
plt.title('Label distribution')
plt.show()
```

```
FULL

derived_label
spiral        118947
elliptical     68725
ambiguous      35111
edge-on        16115
merger           674
Name: count, dtype: int64
```



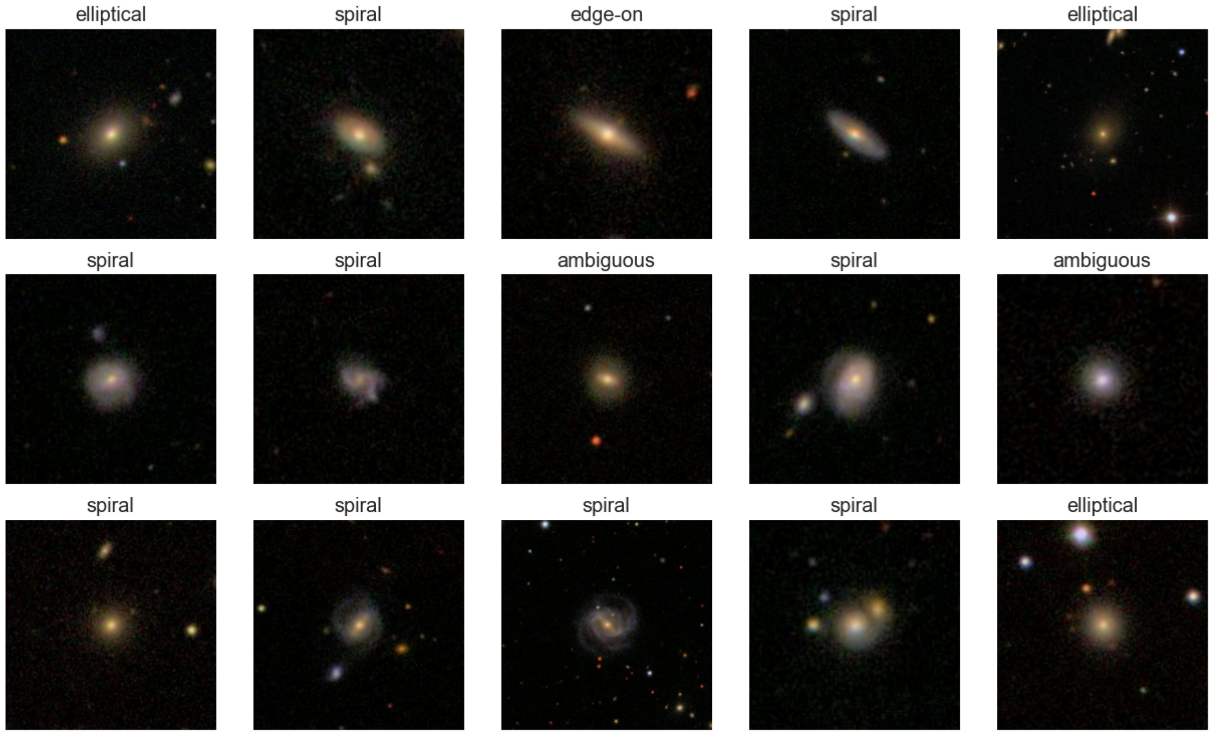

```
SAMPLE

derived_label
spiral        250
elliptical    250
edge-on       250
merger        250
Name: count, dtype: int64
```



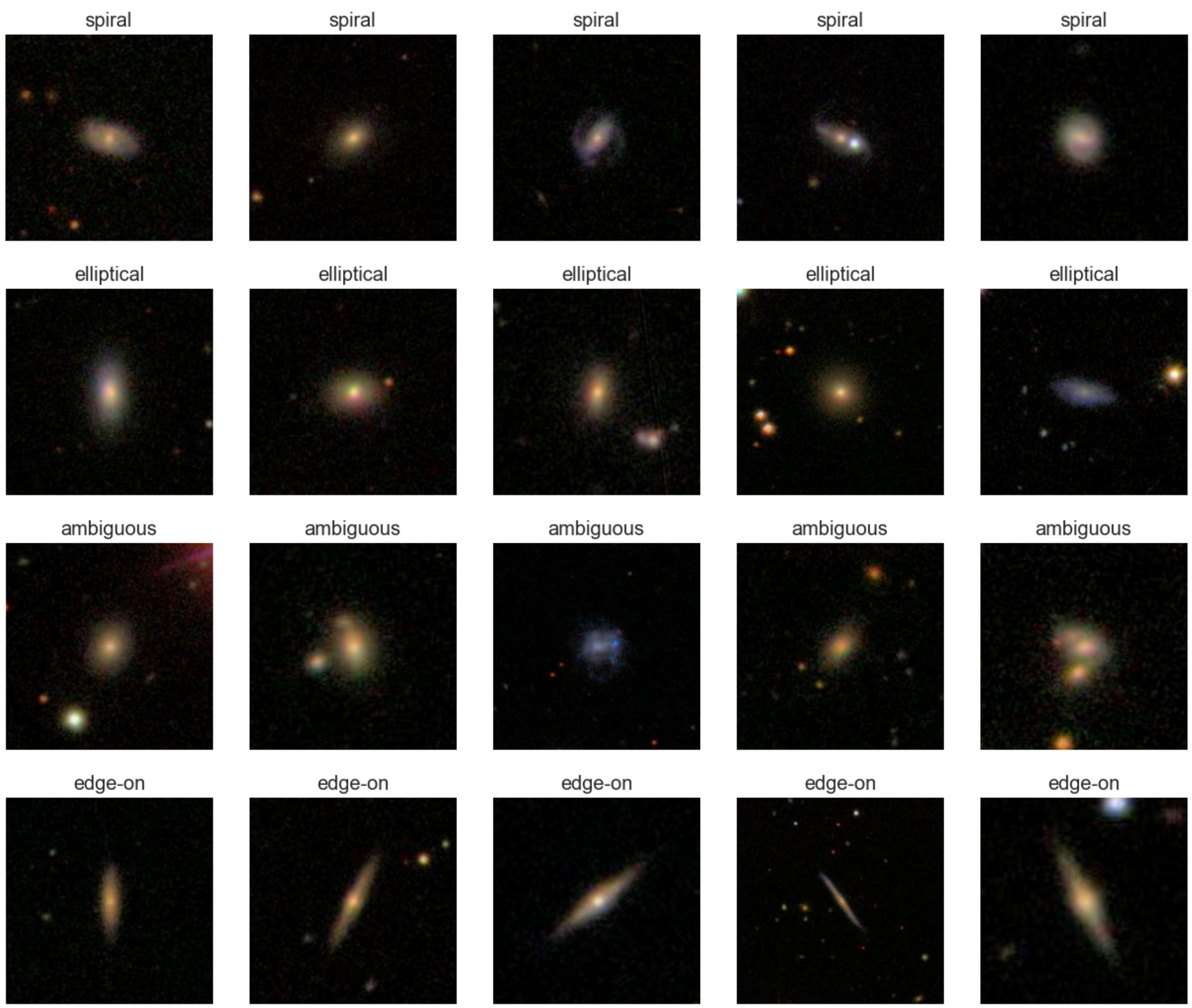
Indeed, almost half of entries were classified as spiral, a quarter were elliptical, and there were much less ambiguous and edge-on ones. Merger galaxies, surprisingly, had only 674 entries (~0.3%).

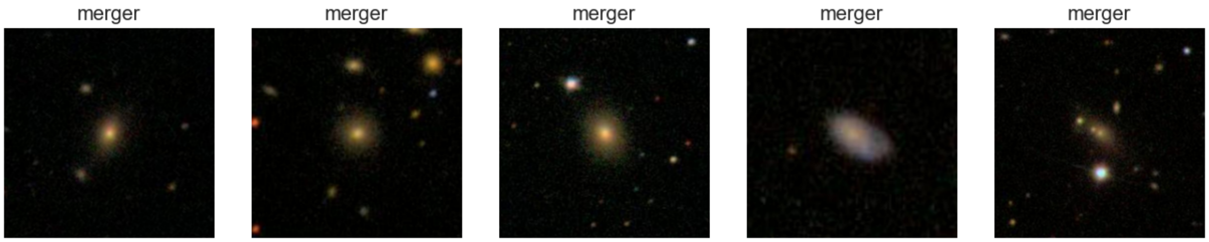
In [38]:
```
#[partially AI-generated function]
def show_images(rows=3, cols=5, label=None):
    chosen = dfm if label is None else dfm[dfm['derived_label']==label]
    chosen = chosen.sample(min(len(chosen), rows*cols), random_state=5629)
    fig, axs = plt.subplots(rows, cols, figsize=(cols*2.5, rows*2.5))
    axs = axs.ravel()
    for ax, (_, row) in zip(axs, chosen.iterrows()):
        img = Image.open(str(PROJECT_ROOT / row["filepath"])).convert('RGB').resize
        ax.imshow(img)
        ax.axis('off')
        ax.set_title(str(row['derived_label'])[:20])
    plt.tight_layout()
    plt.show()
print("A couple of random images with labels:\n")
show_images()
print("Examples of each class:\n")
show_images(rows=1, label=dfm['derived_label'].value_counts().index[0])
show_images(rows=1, label=dfm['derived_label'].value_counts().index[1])
show_images(rows=1, label=dfm['derived_label'].value_counts().index[2])
show_images(rows=1, label=dfm['derived_label'].value_counts().index[3])
show_images(rows=1, label=dfm['derived_label'].value_counts().index[4])
```

```
A couple of random images with labels:
```




```
Examples of each class:
```





The galaxies in the sample are very varied and have distinct features. All the thumbnails are 224 by 224 pixels, 3 color channels. Artifacts can be rarely seen: chromatic aberration, gravitational lensing. Additionally, the objects are very rarely alone in the photos: this could negatively impact training. However, if the noise and out of place objects are evenly distributed, the models may learn to ignore it.

Captions

As for the captions, captions_sample.csv contains generated captions for every class. Most were automatically generated, and a few were written by hand by me. For more detailed information about caption generation, see notebook 03_baselines. Now, let's focus on the statistical evidence.

In [39]:
```
captions_filepath = DATA_PATH / "captions" / "captions_sample.csv"
dfc = pd.read_csv(captions_filepath)
print("Here are some random captions:\n")
for c in dfc['caption'].dropna().sample(min(10, dfc['caption'].dropna().shape[0]),
    print("-", c)
print("Here is the average caption length:")
print(sum(dfc['caption'].dropna().map(len).tolist())/len(dfc['caption'].dropna()))
```

```
Here are some random captions:

- galaxy seen edge-on, with a conspicuous round bulge
- interacting/merging spiral galaxy with a prominent bulge
- elliptical galaxy with a conspicuous bulge
- rounded/cigar-shaped spiral galaxy in a merger
- rounded/cigar-shaped spiral galaxy seen edge-on
- elliptical galaxy with a noticeable bulge
- rounded/cigar-shaped edge-on spiral galaxy
- rounded/cigar-shaped edge-on spiral galaxy
- galaxy in a merger
- rounded/cigar-shaped galaxy in a merger, with a noticeable round bulge
Here is the average caption length:
58.308
```

Let's look at the numeric features in the dataset:

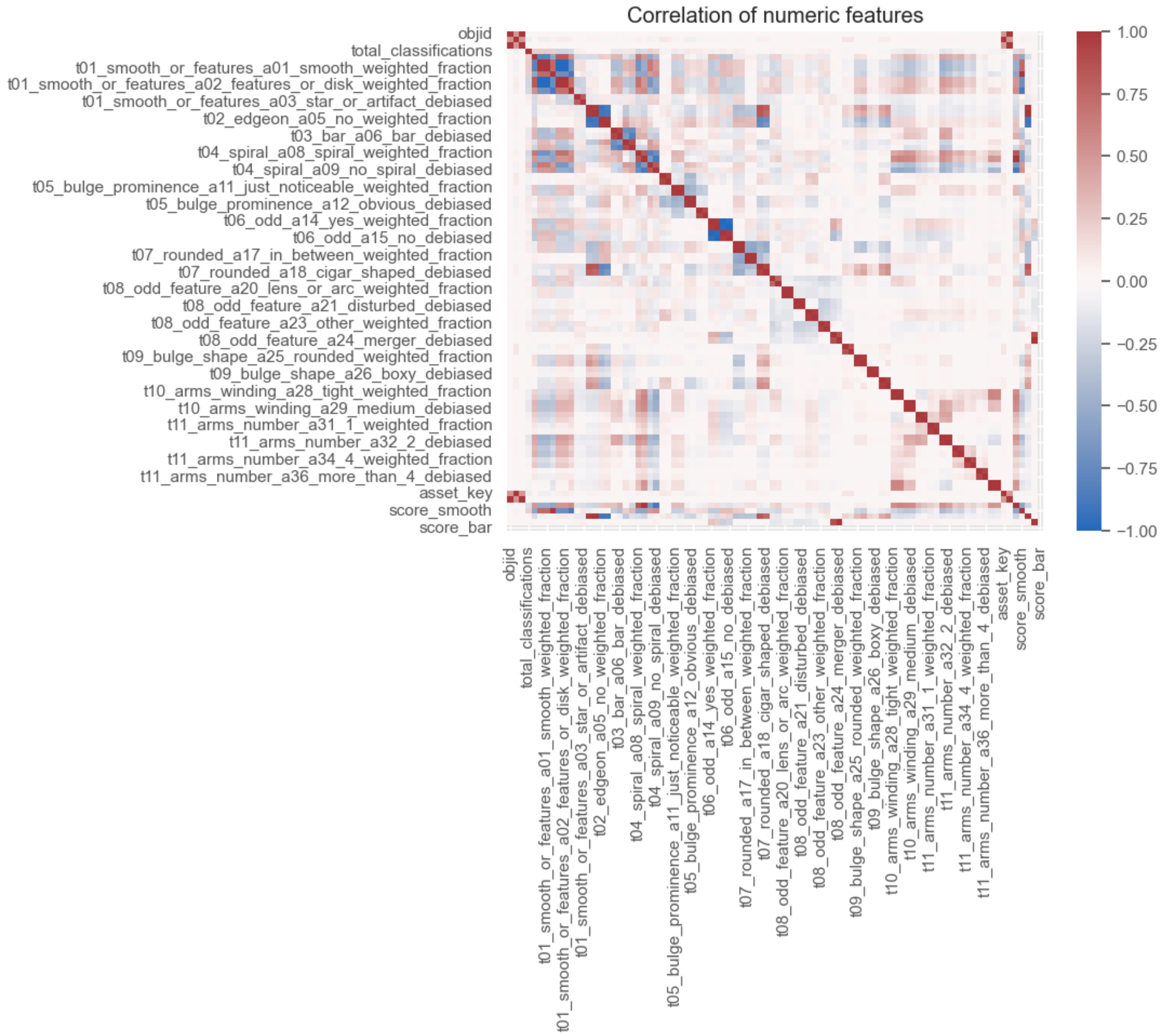
In [40]:
```
print("FULL SET:\n")
num_cols_listm = dfm.select_dtypes(['int64', 'float64']).columns.tolist()
print("Total numeric columns:", len(num_cols_listm))
display(dfm[num_cols_listm].describe())
plt.figure(figsize=(8,6))
```

```
sns.heatmap(dfm[num_cols_listm].corr(), fmt=".2f", cmap='vlag', center=0)
plt.title('Correlation of numeric features')
plt.show()

print("\nSAMPLE:\n")
num_cols_list = df.select_dtypes(['int64', 'float64']).columns.tolist()
print("Total numeric columns:", len(num_cols_list))
display(df[num_cols_list].describe())
plt.figure(figsize=(8,6))
sns.heatmap(df[num_cols_list].corr(), fmt=".2f", cmap='vlag', center=0)
plt.title('Correlation of numeric features')
plt.show()
```

```
FULL SET:

Total numeric columns: 88
```

	objid	asset_id	dr7objid	total_classifications	total_votes	t01_sr
count	2.395720e+05	239572.000000	2.395720e+05	239572.00000	239572.000000	
mean	5.878182e+17	141803.619705	5.878182e+17	42.57144	179.063179	
std	1.827193e+14	81498.732113	1.827193e+14	5.85539	60.704100	
min	5.877230e+17	3.000000	5.877230e+17	16.00000	45.000000	
25%	5.877327e+17	71608.750000	5.877327e+17	39.00000	140.000000	
50%	5.877393e+17	140253.500000	5.877393e+17	43.00000	156.000000	
75%	5.877429e+17	212400.250000	5.877429e+17	46.00000	196.000000	
max	5.888489e+17	295304.000000	5.888489e+17	79.00000	604.000000	

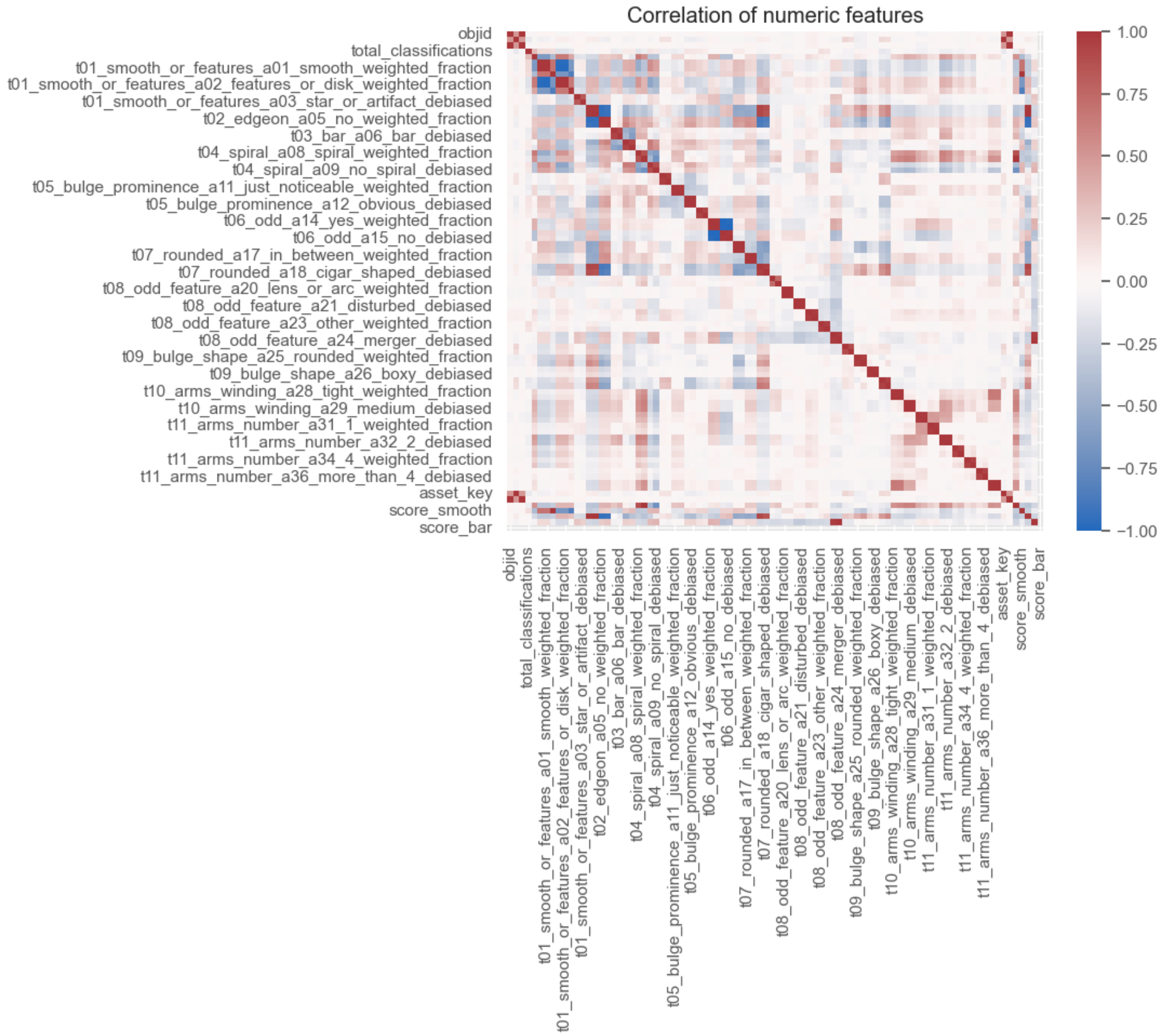
8 rows × 88 columns




```
SAMPLE:

Total numeric columns: 88
```

	objid	asset_id	dr7objid	total_classifications	total_votes	t01_smo
count	1.000000e+03	1000.000000	1.000000e+03	1000.000000	1000.000000	
mean	5.878114e+17	140454.676000	5.878114e+17	42.822000	168.478000	
std	1.790412e+14	82977.365892	1.790412e+14	5.532352	50.373058	
min	5.877230e+17	68.000000	5.877230e+17	22.000000	81.000000	
25%	5.877327e+17	71215.500000	5.877327e+17	40.000000	137.750000	
50%	5.877391e+17	136708.500000	5.877391e+17	43.000000	154.000000	
75%	5.877426e+17	215987.750000	5.877426e+17	46.000000	182.000000	
max	5.888489e+17	295148.000000	5.888489e+17	73.000000	448.000000	

8 rows × 88 columns



Analyzing the heatmap, almost no features show sophisticated correlation, meaning that none of the columns of the dataset are redundant.

Additionally, the average values in both datasets are really close, meaning that the sample is a good representative of the entire thing.

Now, a check for corrupted images:

In [42]:
```
issues_m = []
for _, r in dfm.iterrows():
    path = None
    if pd.notna(r['filepath']):
        path = r['filepath']
    if path is None or not os.path.exists(path):
        issues_m.append(r.get('objid'))
print("Missing or non-existent paths in full dataset:", len(issues_m))
#print(issues_m)
issues = []
for _, r in df.iterrows():
    path = r['filepath']
    if path is None or not os.path.exists(path):
        issues.append((r.get('id',None), path))
```

```python
print("Missing or non-existent paths in sample:", len(issues))
#print(issues)
```

```
Missing or non-existent paths in full dataset: 239572
Missing or non-existent paths in sample: 1000
```

No corrupted images were found (in the sample)!

Initially, the 122 missing filepaths in the full dataset still existed.

Previously:

Missing or non-existent paths in full dataset: 122

[587722982290620479, 587725471205490852, 587725471205556327, 587725471205556424, 587725577498591551, 587726014554636629, 587726014554702078, 587728906098180287, 587728906098180522, 587728931332948214, 587728931333013972, 587729157907939465, 587729386061561998, 587729386061627642, 587729386061627701, 587729781467316737, 587732053773910272, 587732701259694189, 587732701259759718, 587732701259759740, 587735348573896849, 587736479207391416, 587736543625150556, 587736619329651020, 587736900376526998, 587736900376527023, 587736945742381151, 587736945742381457, 588007004198863224, 588010878770020490, 588010878770020496, 588010879306170542, 588010879306170548, 588010879306235941, 588010879306235980, 588010879306236089, 588010879306301459, 588013382718259801, 588013382718324989, 588013382718325277, 588013382718325328, 588013382721142962, 588013382721208796, 588017627783299332, 588017627783299340, 588017627783364868, 588017702952960310, 588017704562852063, 588017710975156345, 588017724394111043, 588017726012588264, 588848899389456487, 588848899389456617, 588848899389522032, 587726100416692571, 587729158434062487, 587729387686068315, 587732484904124593, 587732701259628661, 588017702952894724, 588017726012653729, 588848899389456658, 587730846353261027, 587730846354965290, 587730846886724500, 587730847427985641, 587730847962039063, 587730848498975509, 587730848501072107, 587731173307384385, 587731173843731297, 587731174917669027, 587731174918980260, 587731185114087993, 587731185114088161, 587731185114088316, 587731185129291992, 587731185649910175, 587731185658888420, 587731185669374122, 587731186192744693, 587731186192744702, 587731186192810164, 587731186194055543, 587731186209718282, 587731187275923677, 587731187804995856, 587731187810893999, 587731187810894085, 587731187810894087, 587731512070176839, 587731512070177108, 587731512611438744, 587731512620220559, 587731513145688256, 587731513151914131, 587731513151914161, 587731513690816599, 587731514229850204, 587734304341426500, 587734304877052080, 587734305413333309, 587734305413333343, 587734305414381601, 587734305419362425, 587734305956167817, 588015507664535599, 588015507665125409, 588015507674955940, 588015507674955948, 588015507674955959, 588015507679805636, 588015508189479460, 588015508736114702, 588015508757151905, 588015509287862526, 588015509812347028, 588015509812347075, 588015509825650890, 588015509825716307, 588015509825716346, 588015510342008936]

Missing or non-existent paths in sample: 0 []

I dropped them with a command, so now there are no missing filepaths.

In the following steps (preprocessing), I will split the dataset into training (70%) and validation (20%) split, and also leave a small fraction (10%) for posterior evaluation. For the baseline model, the input will consist of images-only. Later I plan on adding column data to see the difference.

Summary

What can be inferred from the dataset:

- Dataset size: 240 000
- Label classes: spiral, elliptical, edge-on, merger, ambiguous
- No major quality issues found
- preprocessing lies ahead