# DonorsChoose

December 18, 2025

## 1 DonorsChoose Project Approval Analysis

**Problem statement:**

DonorsChoose.org, a platform dedicated to funding classroom projects, faces significant challenges in efficiently and consistently vetting an increasing number of project proposals. With an anticipated influx of close to 500,000 proposals next year, the organization needs to address the following key issues:

- **Scalability:** How can DonorsChoose.org scale its current manual screening processes and resources to handle the projected volume of 500,000 project proposals, ensuring timely and efficient posting?
- **Consistency:** How can DonorsChoose.org enhance the consistency of project vetting across a diverse group of volunteers to ensure a uniform and fair experience for all teachers submitting proposals?
- **Resource Allocation:** How can DonorsChoose.org optimize the use of volunteer time by focusing their efforts on proposals that require the most assistance?

To address these challenges, the objective of this case study is to develop a predictive model that can determine the likelihood of a project proposal being approved.

This model will utilize the text of project descriptions along with additional metadata about the project, teacher, and school. By predicting the approval status of each proposal, DonorsChoose.org can - Streamline the vetting process - Ensuring that projects likely to need further review are prioritized, thereby improving overall efficiency and consistency in project approval.

### 1.1 Importing data and libraries

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

[ ]:
```
!gdown 1SGjaC1pNK-Xnc9DMuQQSnxQwB7ROzsRo
!gdown 1uM8whn9H8L0iPtbLXgIch8M3fPObC9Tm
```

```
Downloading…
From (original): https://drive.google.com/uc?id=1SGjaC1pNK-
```

```
Xnc9DMuQQSnxQwB7ROzsRo
From (redirected): https://drive.google.com/uc?id=1SGjaC1pNK-
Xnc9DMuQQSnxQwB7ROzsRo&confirm=t&uuid=c91bf20c-554e-4835-b7d8-2666f5959804
To: /content/resources.csv
100% 127M/127M [00:00<00:00, 128MB/s]
Downloading…
From (original):
https://drive.google.com/uc?id=1uM8whn9H8L0iPtbLXgIch8M3fPObC9Tm
From (redirected): https://drive.google.com/uc?id=1uM8whn9H8L0iPtbLXgIch8M3fPObC
9Tm&confirm=t&uuid=15a615f4-56ea-4ab9-b5c8-3ea0ef653f9a
To: /content/train_data.csv
100% 200M/200M [00:02<00:00, 73.1MB/s]
```

[ ]:
```python
resources = pd.read_csv('/content/resources.csv')
projects = pd.read_csv('/content/train_data.csv')
```

[ ]:
```python
projects.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 109248 entries, 0 to 109247
Data columns (total 16 columns):
 #   Column                                        Non-Null Count   Dtype
---  ------                                        --------------   -----
 0   id                                            109248 non-null  object
 1   teacher_id                                    109248 non-null  object
 2   teacher_prefix                                109245 non-null  object
 3   school_state                                  109248 non-null  object
 4   project_submitted_datetime                    109248 non-null  object
 5   project_grade_category                        109248 non-null  object
 6   project_subject_categories                    109248 non-null  object
 7   project_subject_subcategories                 109248 non-null  object
 8   project_title                                 109248 non-null  object
 9   project_essay_1                               109248 non-null  object
 10  project_essay_2                               109248 non-null  object
 11  project_essay_3                               3758 non-null    object
 12  project_essay_4                               3758 non-null    object
 13  project_resource_summary                      109248 non-null  object
 14  teacher_number_of_previously_posted_projects  109248 non-null  int64
 15  project_is_approved                           109248 non-null  int64
dtypes: int64(2), object(14)
memory usage: 13.3+ MB
```

[ ]:
```python
projects.head()
```

[ ]:
```
        id                        teacher_id teacher_prefix school_state  \
0  p253737  c90749f5d961ff158d4b4d1e7dc665fc           Mrs.           IN
1  p258326  897464ce9ddc600bced1151f324dd63a            Mr.           FL
```

```
2  p182444  3465aaf82da834c0582ebd0ef8040ca0           Ms.           AZ
3  p246581  f3cb9bffbba169bef1a77b243e620b60          Mrs.           KY
4  p104768  be1f7507a41f8479dc06f047086a39ec          Mrs.           TX

  project_submitted_datetime project_grade_category  \
0          05-12-2016 13:43          Grades PreK-2
1          25-10-2016 09:22             Grades 6-8
2          31-08-2016 12:03             Grades 6-8
3          06-10-2016 21:16          Grades PreK-2
4          11-07-2016 01:10          Grades PreK-2

          project_subject_categories     project_subject_subcategories  \
0                Literacy & Language                      ESL, Literacy
1   History & Civics, Health & Sports  Civics & Government, Team Sports
2                    Health & Sports    Health & Wellness, Team Sports
3  Literacy & Language, Math & Science            Literacy, Mathematics
4                     Math & Science                        Mathematics

                                     project_title  \
0   Educational Support for English Learners at Home
1              Wanted: Projector for Hungry Learners
2  Soccer Equipment for AWESOME Middle School Stu…
3                             Techie Kindergarteners
4                             Interactive Math Tools

                                   project_essay_1  \
0  My students are English learners that are work…
1  Our students arrive to our school eager to lea…
2  \r\n\"True champions aren't always the ones th…
3  I work at a unique school filled with both ESL…
4  Our second grade classroom next year will be m…

                                   project_essay_2 project_essay_3  \
0  \"The limits of your language are the limits o…            NaN
1  The projector we need for our school is very c…            NaN
2  The students on the campus come to school know…            NaN
3  My students live in high poverty conditions wi…            NaN
4  For many students, math is a subject that does…            NaN

  project_essay_4                         project_resource_summary  \
0            NaN  My students need opportunities to practice beg…
1            NaN  My students need a projector to help with view…
2            NaN  My students need shine guards, athletic socks,…
3            NaN  My students need to engage in Reading and Math…
4            NaN  My students need hands on practice in mathemat…

   teacher_number_of_previously_posted_projects  project_is_approved
```

```
0                                                     0          0
1                                                     7          1
2                                                     1          0
3                                                     4          1
4                                                     1          1
```

[ ]:
```
resources.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1541272 entries, 0 to 1541271
Data columns (total 4 columns):
 #   Column       Non-Null Count    Dtype
---  ------       --------------    -----
 0   id           1541272 non-null  object
 1   description  1540980 non-null  object
 2   quantity     1541272 non-null  int64
 3   price        1541272 non-null  float64
dtypes: float64(1), int64(1), object(2)
memory usage: 47.0+ MB
```

[ ]:
```
resources.head()
```

[ ]:
```
        id                                        description  quantity  \
0  p233245  LC652 - Lakeshore Double-Space Mobile Drying Rack         1
1  p069063        Bouncy Bands for Desks (Blue support pipes)         3
2  p069063  Cory Stories: A Kid's Book About Living With Adhd         1
3  p069063  Dixon Ticonderoga Wood-Cased #2 HB Pencils, Bo…         2
4  p069063  EDUCATIONAL INSIGHTS FLUORESCENT LIGHT FILTERS…         3

    price
0  149.00
1   14.95
2    8.45
3   13.59
4   24.95
```

## 1.2 Data Cleaning

[ ]:
```
def column_analysis(df):
  rows = []
  for col in df.columns:
    dtype = df[col].dtype
    null = df[col].isna().sum()
    nunique = df[col].nunique(dropna=True)
    sample_vals = df[col].dropna().astype(str).sample(5).tolist() if df[col].
↪notna().sum() else []
    rows.append({
```

```
        'column': col,
        'dtype': str(dtype),
        'null_count': int(null),
        'nunique': int(nunique),
        'sample_values': '| '.join(sample_vals)
    })
  return pd.DataFrame(rows)
```

[ ]:
```
column_analysis(projects)
```

[ ]:
```
                                         column   dtype  null_count  nunique  \
0                                            id  object           0   109248
1                                    teacher_id  object           0    72168
2                                teacher_prefix  object           3        5
3                                  school_state  object           0       51
4                      project_submitted_datetime  object           0    90885
5                        project_grade_category  object           0        4
6                    project_subject_categories  object           0       51
7                 project_subject_subcategories  object           0      401
8                                 project_title  object           0   100850
9                               project_essay_1  object           0    94319
10                              project_essay_2  object           0   108831
11                              project_essay_3  object      105490     3755
12                              project_essay_4  object      105490     3750
13                     project_resource_summary  object           0   108323
14  teacher_number_of_previously_posted_projects   int64           0      374
15                          project_is_approved   int64           0        2

                                      sample_values
0          p102226| p037640| p107683| p119596| p146084
1   b1e564ffe6d97c7776fe1029d14e1ad2| 22271ffa9dc1…
2                      Ms.| Teacher| Mrs.| Mrs.| Ms.
3                                 CO| IL| CT| FL| OK
4   06-07-2016 23:27| 17-11-2016 19:14| 07-11-2016…
5   Grades 3-5| Grades 6-8| Grades 3-5| Grades Pre…
6   Health & Sports| Math & Science, Special Needs…
7   Early Development, Health & Life Science| Lite…
8   Extra! Extra! Help Us Read All About It!| Plea…
9   My school is a small elementary school in Spri…
10  I've tried my best to make my classroom into a…
11  The books will be used as mentor text to writi…
12  Donations to our makerspace project will help …
13  My students need 12 bouncy bands for their des…
14                                 3| 3| 16| 2| 11
15                                   1| 1| 1| 1| 1
```

[ ]:
```
projects.shape
```

[ ]: (109248, 16)

[ ]:
```
projects[projects['teacher_prefix'].isna()]
```

[ ]:
```
             id                        teacher_id teacher_prefix school_state  \
7820   p180947  834f75f1b5e24bd10abe9c3dbf7ba12f            NaN           CA
30368  p002730  339bd5a9e445d68a74d65b99cd325397            NaN           SC
57654  p197901  e4be6aaaa887d4202df2b647fbfc82bb            NaN           PA

      project_submitted_datetime project_grade_category  \
7820            04-11-2016 00:15             Grades 3-5
30368           09-05-2016 09:38            Grades 9-12
57654           03-06-2016 10:15             Grades 3-5

                project_subject_categories      project_subject_subcategories  \
7820   Literacy & Language, Math & Science  Literature & Writing, Mathematics
30368                  Literacy & Language               Literature & Writing
57654  Literacy & Language, Math & Science              Literacy, Mathematics

                                     project_title  \
7820   1:7 Increasing Tech to Decrease Achievement Gaps
30368                           iPads for STEM Stations
57654                                   Document Camera

                                         project_essay_1  \
7820   The children at Anna Yates Elementary school a…
30368  Within the next 20 years, every job will invol…
57654  Students at Robertsdale Elementary live in a l…

                                         project_essay_2  \
7820   My goal is to bring in 1 laptop for every 7 st…
30368  The students in our school come from a wide va…
57654  This SMART Document Camera will improve my stu…

                                         project_essay_3  \
7820                                                 NaN
30368  Students will use the iPad station for individ…
57654                                                NaN

                                         project_essay_4  \
7820                                                 NaN
30368  Your generosity will allow my students to work…
57654                                                NaN

                                project_resource_summary  \
7820   My students need a classroom laptop that is ju…
30368        My students need 5 iPads for STEM stations.
```

```
57654  My students need a Smart Document Camera to en…

       teacher_number_of_previously_posted_projects  project_is_approved
7820                                              1                    1
30368                                             0                    1
57654                                             0                    1
```

[ ]:
```
projects[projects['teacher_id'].isin(['834f75f1b5e24bd10abe9c3dbf7ba12f',
 ↪'339bd5a9e445d68a74d65b99cd325397', 'e4be6aaaa887d4202df2b647fbfc82bb'])]
```

[ ]:
```
            id                        teacher_id teacher_prefix school_state  \
7820   p180947  834f75f1b5e24bd10abe9c3dbf7ba12f            NaN           CA
30368  p002730  339bd5a9e445d68a74d65b99cd325397            NaN           SC
57654  p197901  e4be6aaaa887d4202df2b647fbfc82bb            NaN           PA

      project_submitted_datetime project_grade_category  \
7820            04-11-2016 00:15            Grades 3-5
30368           09-05-2016 09:38           Grades 9-12
57654           03-06-2016 10:15            Grades 3-5

                project_subject_categories      project_subject_subcategories  \
7820   Literacy & Language, Math & Science  Literature & Writing, Mathematics
30368                  Literacy & Language               Literature & Writing
57654  Literacy & Language, Math & Science              Literacy, Mathematics

                                   project_title  \
7820   1:7 Increasing Tech to Decrease Achievement Gaps
30368                           iPads for STEM Stations
57654                                   Document Camera

                                    project_essay_1  \
7820   The children at Anna Yates Elementary school a…
30368  Within the next 20 years, every job will invol…
57654  Students at Robertsdale Elementary live in a l…

                                    project_essay_2  \
7820   My goal is to bring in 1 laptop for every 7 st…
30368  The students in our school come from a wide va…
57654  This SMART Document Camera will improve my stu…

                                    project_essay_3  \
7820                                             NaN
30368  Students will use the iPad station for individ…
57654                                            NaN

                                    project_essay_4  \
7820                                             NaN
```

```
30368  Your generosity will allow my students to work…
57654                                               NaN

                             project_resource_summary  \
7820   My students need a classroom laptop that is ju…
30368        My students need 5 iPads for STEM stations.
57654  My students need a Smart Document Camera to en…

       teacher_number_of_previously_posted_projects  project_is_approved
7820                                              1                    1
30368                                             0                    1
57654                                             0                    1
```

[ ]:
```
projects['teacher_prefix'].value_counts()
```

[ ]:
```
teacher_prefix
Mrs.       57269
Ms.        38955
Mr.        10648
Teacher     2360
Dr.           13
Name: count, dtype: int64
```

[ ]:
```
projects['teacher_prefix'].fillna(projects['teacher_prefix'].mode()[0],␣
 ↪inplace=True)
```

[ ]:
```
projects['project_essay_3'].fillna('', inplace=True)
projects['project_essay_4'].fillna('', inplace=True)
```

- replace the nulls of text columns with emplty string

[ ]:
```
projects.isna().sum().sum()
```

[ ]:
```
np.int64(0)
```

[ ]:
```
projects["project_submitted_datetime"] = pd.to_datetime(
    projects["project_submitted_datetime"], format="%d-%m-%Y %H:%M"
)
```

[ ]:
```
column_analysis(projects)
```

[ ]:
```
                        column           dtype  null_count  \
0                           id          object           0
1                   teacher_id          object           0
2               teacher_prefix          object           0
3                 school_state          object           0
4   project_submitted_datetime  datetime64[ns]           0
```

```
5                      project_grade_category         object           0
6                  project_subject_categories         object           0
7               project_subject_subcategories         object           0
8                               project_title         object           0
9                             project_essay_1         object           0
10                            project_essay_2         object           0
11                            project_essay_3         object           0
12                            project_essay_4         object           0
13                   project_resource_summary         object           0
14  teacher_number_of_previously_posted_projects       int64           0
15                        project_is_approved          int64           0

    nunique                                     sample_values
0    109248        p210561| p103029| p077989| p138405| p078686
1     72168  636d8733dda6da2669883434e706afb7| 6e3c8cf8044d…
2         5                             Ms.| Ms.| Mr.| Ms.| Mr.
3        51                                  MD| OK| MI| GA| PA
4     90885  2017-01-04 18:03:00| 2016-05-06 09:45:00| 2016…
5         4  Grades 3-5| Grades PreK-2| Grades 3-5| Grades …
6        51  Literacy & Language| Math & Science| Literacy …
7       401  Literacy, Literature & Writing| Literature & W…
8    100850  Safe Sensory Supplies| Comfy Cozy Classroom| T…
9     94319  I am so excited to welcome 60 new students to …
10   108831  We need to equip our library with a wide range…
11     3756                                             | | | |
12     3751  | | This donation would greatly improve my stu…
13   108323  My students need Wobble Chairs to help them si…
14      374                                        0| 2| 1| 1| 0
15        2                                        1| 1| 1| 1| 1
```

[ ]:
```
resources.shape
```

[ ]: (1541272, 4)

[ ]:
```
column_analysis(resources)
```

[ ]:
```
        column    dtype  null_count  nunique  \
0           id   object           0   260115
1  description   object         292   332928
2     quantity    int64           0      208
3        price  float64           0    26890

                                    sample_values
0      p126211| p199069| p040798| p030621| p142987
1  Enrique's Journey (The Young Adult Adaptation)…
2                                    2| 1| 4| 1| 1
3                    12.4| 74.82| 20.43| 6.29| 6.3
```

[ ]:
```
resources[resources['description'].isna()][['id', 'description']]
```

[ ]:
```
              id description
37603    p194324         NaN
37604    p194324         NaN
37605    p194324         NaN
37606    p194324         NaN
44304    p084588         NaN
…          …          …
1277794  p042527         NaN
1289873  p033486         NaN
1301428  p227836         NaN
1304563  p083954         NaN
1333459  p118647         NaN

[292 rows x 2 columns]
```

[ ]:
```
resources[resources['id']=='p194324']
```

[ ]:
```
            id                                description  quantity  price
37603  p194324                                        NaN         1  73.16
37604  p194324                                        NaN         1  11.69
37605  p194324                                        NaN         1  64.30
37606  p194324                                        NaN         1  15.52
37607  p194324                      Bullying (10 Bk Set)         1  65.79
37608  p194324             Character Education (6 Bk Set)         1  35.42
37609  p194324                     Civil Rights (4 Bk Set)         1  31.05
37610  p194324  Spanish Heritage - Nonfiction (10 Bk Set)         1  63.61
```

[ ]:
```
resources['description'].fillna('', inplace=True)
```

- we can impute the nulls of text column with empty string as no common id have common descriptions.

[ ]:
```
resources.rename(columns={'price': 'unit_price'}, inplace=True)
```

[ ]:
```
resources['resource_cost'] = resources['unit_price'] * resources['quantity']
```

[ ]:
```
column_analysis(resources)
```

[ ]:
```
          column    dtype  null_count  nunique  \
0             id   object           0   260115
1    description   object           0   332929
2       quantity    int64           0      208
3     unit_price  float64           0    26890
4  resource_cost  float64           0    50356
```

```
                                        sample_values
0       p163082| p151483| p112614| p056330| p245321
1  Scotch Thermal Laminator Combo Pack, Includes …
2                                      1| 5| 1| 1| 1
3                    174.78| 9.72| 17.99| 6.9| 99.99
4                       69.95| 7.06| 9.25| 8.47| 6.0
```

## 1.3 Text Processing

### 1.3.1 resource description

[ ]:
```python
resources.head()
```

[ ]:
```
        id                                      description  quantity  \
0  p233245  LC652 - Lakeshore Double-Space Mobile Drying Rack         1
1  p069063        Bouncy Bands for Desks (Blue support pipes)         3
2  p069063  Cory Stories: A Kid's Book About Living With Adhd         1
3  p069063  Dixon Ticonderoga Wood-Cased #2 HB Pencils, Bo…         2
4  p069063  EDUCATIONAL INSIGHTS FLUORESCENT LIGHT FILTERS…         3

   unit_price  resource_cost
0      149.00         149.00
1       14.95          44.85
2        8.45           8.45
3       13.59          27.18
4       24.95          74.85
```

- There are so many descriptions i.e., high cardinality
- Even same item might have different descriptions and hence better do clustering on sbert embeddings such that we can group similar items.

[ ]:
```python
import re

def sbert_clean(text):
    if not isinstance(text, str):
        return ""
    text = text.strip()                   # remove extra spaces at ends
    text = re.sub(r'\s+', ' ', text)      # collapse multiple spaces
    return text.lower()                   # SBERT works fine with lowercase
```

[ ]:
```python
resources["cleaned_description"] = resources["description"].apply(sbert_clean)
```

[ ]:
```python
resources.head()
```

[ ]:
```
        id                                      description  quantity  \
0  p233245  LC652 - Lakeshore Double-Space Mobile Drying Rack         1
1  p069063        Bouncy Bands for Desks (Blue support pipes)         3
```

```
2  p069063  Cory Stories: A Kid's Book About Living With Adhd         1
3  p069063  Dixon Ticonderoga Wood-Cased #2 HB Pencils, Bo…         2
4  p069063  EDUCATIONAL INSIGHTS FLUORESCENT LIGHT FILTERS…         3

   unit_price  resource_cost  \
0      149.00         149.00
1       14.95          44.85
2        8.45           8.45
3       13.59          27.18
4       24.95          74.85

                               cleaned_description
0  lc652 - lakeshore double-space mobile drying rack
1        bouncy bands for desks (blue support pipes)
2  cory stories: a kid's book about living with adhd
3  dixon ticonderoga wood-cased #2 hb pencils, bo…
4  educational insights fluorescent light filters…
```

[ ]:
```python
import torch
device = "cuda" if torch.cuda.is_available() else "cpu"
device
```

[ ]:
```
'cuda'
```

[ ]:
```python
cleaned_descriptions = resources['cleaned_description'].astype(str).tolist()
```

[ ]:
```python
from sentence_transformers import SentenceTransformer

# Load SBERT
resources_sbert_model = SentenceTransformer("all-MiniLM-L6-v2")

# sbert embeddings
resources_embeddings = resources_sbert_model.encode(cleaned_descriptions,
                                                    device=device,
                                                    show_progress_bar=True)
```

```
modules.json:   0%|          | 0.00/349 [00:00<?, ?B/s]

config_sentence_transformers.json:   0%|          | 0.00/116 [00:00<?, ?B/s]

README.md: 0.00B [00:00, ?B/s]

sentence_bert_config.json:   0%|          | 0.00/53.0 [00:00<?, ?B/s]

config.json:   0%|          | 0.00/612 [00:00<?, ?B/s]

model.safetensors:   0%|          | 0.00/90.9M [00:00<?, ?B/s]

tokenizer_config.json:   0%|          | 0.00/350 [00:00<?, ?B/s]

vocab.txt: 0.00B [00:00, ?B/s]
```

```
tokenizer.json: 0.00B [00:00, ?B/s]

special_tokens_map.json:   0%|          | 0.00/112 [00:00<?, ?B/s]

config.json:   0%|          | 0.00/190 [00:00<?, ?B/s]

Batches:   0%|          | 0/48165 [00:00<?, ?it/s]
```

[ ]:
```
resources_embeddings.shape
```

[ ]: (1541272, 384)

[ ]:
```
from sklearn.decomposition import PCA

resources_pca = PCA(n_components=100, random_state=42)

resources_embeddings_pca = resources_pca.fit_transform(resources_embeddings)
```

[ ]:
```
resources_pca.explained_variance_ratio_.sum()
```

[ ]: np.float32(0.7220856)

[ ]:
```
!pip install faiss-cpu --quiet
```

```
                              23.7/23.7 MB
20.0 MB/s eta 0:00:00
```

[ ]:
```
import faiss

d = resources_embeddings_pca.shape[1]
k = 30

resources_kmeans = faiss.Kmeans(d=d, k=k, niter=20, verbose=True)

# fit
resources_kmeans.train(resources_embeddings_pca)

# labels
_, resources_kmeans_labels = resources_kmeans.index.
  ↪search(resources_embeddings_pca, 1)
resources_kmeans_labels = resources_kmeans_labels.flatten()

# centroids
resources_kmeans_centroids = resources_kmeans.centroids
```

[ ]:
```
resources_kmeans_labels
```

[ ]: array([ 7, 19,  3, …, 24, 21,  4])

[ ]:
```
resources_kmeans_labels.shape
```

[ ]:
```
(1541272,)
```

[ ]:
```
resources['kmeans_label'] = resources_kmeans_labels
```

[ ]:
```
resources.head()
```

[ ]:
```
        id                                        description  quantity  \
0  p233245  LC652 - Lakeshore Double-Space Mobile Drying Rack         1
1  p069063        Bouncy Bands for Desks (Blue support pipes)         3
2  p069063  Cory Stories: A Kid's Book About Living With Adhd         1
3  p069063  Dixon Ticonderoga Wood-Cased #2 HB Pencils, Bo…         2
4  p069063  EDUCATIONAL INSIGHTS FLUORESCENT LIGHT FILTERS…         3

   unit_price  resource_cost  \
0      149.00         149.00
1       14.95          44.85
2        8.45           8.45
3       13.59          27.18
4       24.95          74.85

                                 cleaned_description  kmeans_label
0  lc652 - lakeshore double-space mobile drying rack             7
1        bouncy bands for desks (blue support pipes)            19
2  cory stories: a kid's book about living with adhd             3
3  dixon ticonderoga wood-cased #2 hb pencils, bo…             9
4  educational insights fluorescent light filters…            23
```

[ ]:
```
resources['kmeans_label'].value_counts()
```

[ ]:
```
kmeans_label
20    135840
12     79249
27     79056
9      72792
11     71141
23     70655
10     62986
3      61830
24     61312
5      60121
29     58404
1      57537
17     54697
14     51174
0      49571
```

```
4       48698
2       47524
7       47064
26      46051
15      43344
16      42120
21      40023
28      38306
19      34860
25      30276
13      28075
18      20141
8       18341
6       18157
22      11927
Name: count, dtype: int64
```

[ ]:
```
import nltk
nltk.download('stopwords')

stop_words = nltk.corpus.stopwords.words('english')

def tfid_clean(text):
  text = text.lower()
  text = re.sub(r'[^a-z ]', '', text)
  text = [word for word in text.split() if word not in stop_words]
  return ' '.join(text)
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data…
[nltk_data]   Unzipping corpora/stopwords.zip.
```

[ ]:
```
resources['cleaned_description'] = resources['cleaned_description'].
 ↪apply(tfid_clean)
```

[ ]:
```
from sklearn.feature_extraction.text import TfidfVectorizer

resoucrces_tfid = TfidfVectorizer(ngram_range=(2,3),
                                  max_features=10000,
                                  min_df=2)

cluster_names = {}
sample_size = 5000

for cl in sorted(resources['kmeans_label'].unique()):
  texts = resources.loc[resources['kmeans_label']==cl, 'cleaned_description'].
 ↪astype(str)
  if len(texts) == 0:
```

```python
        cluster_names[cl] = []
        continue
    if len(texts) > sample_size:
        texts = texts.sample(sample_size, random_state=42)
    X = resoucrces_tfid.fit_transform(texts)

    scores = X.mean(axis=0).A1
    feat = resoucrces_tfid.get_feature_names_out()
    top_idx = scores.argsort()[-20:][::-1]
    cluster_names[cl] = [feat[i] for i in top_idx]

for cl, terms in cluster_names.items():
    print(cl, ":", ", ".join(terms), '\n')
```

```
0 : book set, extra book, extra book set, set gr, book set gr, aa level, gr
library, level extra, level extra book, bk set, level nonfiction, book bin, set
gr library, aa level extra, level nonfiction extra, nonfiction extra, nonfiction
extra book, level book, level book bin, book bin gr

1 : pocket chart, one size, letter size, per pack, laminating pouches, assorted
colors, bean bag, thermal laminating, thermal laminating pouches, storage sack,
atyourseat storage, atyourseat storage sack, write wipe, pockets set, reusable
write wipe, reusable write, write wipe pockets, wipe pockets, wipe pockets set,
school smart

2 : glue sticks, school glue, school glue sticks, tempera paint, oz pack, liquid
tempera paint, liquid tempera, elmers washable, washable liquid, fully washable
liquid, washable liquid tempera, lakeshore fully washable, lakeshore fully,
fully washable, disinfecting wipes, sticks oz, glue sticks oz, paint gallon,
tempera paint gallon, glue stick

3 : min subscriptions, learning resources, issues min, issues min subscriptions,
min subscriptions per, per order, subscriptions per, subscriptions per order,
order issues min, per order issues, order issues, subscriptions grades, min
subscriptions grades, grades min, grades min subscriptions, time kids,
scholastic news, minimum subscriptions, issues minimum, bundle issues minimum

4 : management console, management console license, console license, google edu,
google edu management, edu management console, edu management, document camera,
digital camera, google chrome, wireless activity, chrome os, google chrome os,
os management console, chrome os management, os management, charging station,
activity tracker, protection plan, lcd projector

5 : bk set, master set, dg magnatiles, set set, set pieces, dg magnatiles
master, magnatiles master set, magnatiles master, complete set, piece set,
starter set, classroom supply, color set, box set, class set, boxed set,
assorted colors, reeds box, balls set, ball set
```

6 : toner cartridge, ink cartridge, high yield, ink cartridges, hp xl, original ink, hp black, cartridge black, laserjet toner, original laserjet, original laserjet toner, laserjet toner cartridge, wireless allinone, black original, color ink, allinone printer, hp officejet, original ink cartridge, laserjet pro, hp laserjet

7 : classroom carpet, activity table, lap tray, la classroom carpet, la classroom, option class, cs activity, option class cs, class cs, storage cart, romanoff lap tray, romanoff lap, class cs activity, cs activity table, safco products, top black, activity carpet, area rug, footrest bar, swinging footrest bar

8 : wobble chair, wobble chair blue, chair blue, kore wobble chair, kore wobble, kids kore wobble, kids kore, crbu wobble, crbu wobble chair, chair green, wobble chair green, chair red, wobble chair red, crgr wobble, crgr wobble chair, sitting toddler, sitting toddler preschool, toddler preschool kids, preschool kids, toddler preschool

9 : assorted colors, dry erase, chisel tip, pencil sharpener, dry erase markers, erase markers, fine point, dixon ticonderoga, colored pencils, markers assorted, low odor, electric pencil, dryerase markers, electric pencil sharpener, markers chisel, permanent markers, markers chisel tip, assorted pack, expo lowodor, lowodor dry erase

10 : national geographic, national geographic readers, geographic readers, elephant piggie, elephant piggie book, piggie book, fish tree, little critter, berenstain bears, koala lou, sign beaver, three little, step reading, wild things, wild robot, letsreadandfindout science, little pigs, three little pigs, love dog, read level

11 : pete cat, invisible boy, read level, book thief, harry potter, graphic novel, henry mudge, percy jackson, tree house, magic tree, magic tree house, classic goosebumps, kill mockingbird, star wars, step reading, percy jackson olympians, jackson olympians, fly guy, first read, charlie chocolate

12 : ipad mini, apple ipad, wifi gb, apple ipad mini, celeron gb, space gray, gb space, wifi gb space, gb space gray, mini wifi, ipad mini wifi, gb ram, mini wifi gb, ram gb, gb ram gb, gb ssd, ram gb ssd, ipad air, celeron gb ram, intel celeron

13 : hokki stool, stool blue, hokki stool blue, beanbag seat, stool light, hokki stool light, seat blue, big beanbag, big beanbag seat, stool red, stool black, light blue, stool light blue, hokki stool red, big joe, hokki stool black, beanbag seat blue, little beanbag, little beanbag seat, seat red

14 : write wipe, privacy partition set, partition set, privacy partition, jj privacy partition, jj privacy, complete set, write wipe lapboard, wipe lapboard,

osmo coding set, osmo coding, coding set, alphabet stamps, word building, fishing sightwords, kc write, kc write wipe, sentence strips, write wipe boards, wipe boards

15 : variety pack, oz bags, crackers oz, ounce pack, bags bagsbox, oz bags bagsbox, fruit snacks, pack count, crackers oz bags, variety pack count, mixed fruit, pack oz, welchs mixed, welchs mixed fruit, mixed fruit snacks, oz pack, granola bars, variety pack oz, peanut butter, snacks pouchesbox

16 : osmo genius, genius kit, osmo genius kit, kt stem, stem bundle, kt stem bundle, wonder workshop, lego classic, workshop dash, wonder workshop dash, dash robot, brick box, bundle gr, stem bundle gr, creative brick box, creative brick, stem bundle kgr, bundle kgr, workshop dash robot, activity kit

17 : soccer ball, one size, fitpro ball, adj leg, one color, champion sports, color one, color one size, one color one, jump rope, playground ball, ball set, exercise ball, spalding nba, stability ball, fitness gear, jump ropes, assorted colors, ball pump, hand pump

18 : magnetic letters, write wipe, giant magnetic, magnetic write wipe, magnetic write, classroom magnetic, magnetic letters kit, classroom magnetic letters, letters kit, lc magnetic, jj classroom, jj classroom magnetic, learning resources, dd magnetic, doublesided magnetic, wipe board, write wipe board, magnetic activity, jumbo magnetic, magnetic designer

19 : bouncy bands, support pipes, wobble cushion, stability wobble, stability wobble cushion, balance disc, blue support, blue support pipes, bouncy bands desks, bands desks, black support, black support pipes, bouncy bands chairs, bands chairs, chair blue, core balance, chair blue support, inflated stability, exercise fitness, inflated stability wobble

20 : spanish edition, magnificent thing, one ivan, mouth volcano, big nate, number stars, roller girl, charlottes web, tuck everlasting, nate great, bud buddy, day crayons, chocolate touch, beautiful oops, fault stars, esperanza rising, fly guy, inside back, bad case, crayons quit

21 : melissa doug, fidget toy, fun express, tangle jr, jr original fidget, jr original, original fidget, tangle jr original, original fidget toy, assorted colors, toy set, fidget toy set, educational toy, starter pack, robot toy, ozobot bit, children adults, toy robot, programmable robot, pack programmable robot

22 : staynplay balance ball, staynplay balance, kids staynplay, kids staynplay balance, gaiam kids staynplay, gaiam kids, balance ball, ball lime, balance ball lime, balance ball blue, ball blue, balance ball chair, ball chair, ball grey, balance ball grey, balance ball pink, ball pink, gaiam kids balance, kids balance, kids balance ball

```
23 : stainless steel, master lock, alto saxophone, disc purple, saxophone reeds,
balance disc, round balance, round balance disc, purple cm, bintiva round,
bintiva round balance, disc purple cm, balance disc purple, alto saxophone
reeds, assorted colors, time timer, printer filament, texas instruments,
electric sharpener, school pro

24 : construction paper, paper amp, construction paper amp, assorted colors,
copy paper, inches sheets, lb inches, lb inches sheets, neenah astrobrights,
premium color, astrobrights premium, astrobrights premium color, paper lb,
neenah astrobrights premium, card stock, heavyduty paper, staples copy, staples
copy paper, color paper, wide ruled

25 : listening center, headphones black, onear headphones, volume control, onear
headphones black, multipurpose headphones, headphones volume, headphones volume
control, multipurpose headphones volume, cd player, readytogo listening center,
ce readytogo, readytogo listening, ce readytogo listening, stereo headphones,
bluetooth speaker, headphones set, zx series, player bluetooth, ee hear

26 : board game, complete set, card game, flash cards, folder game, math game,
learning resources, trouble game, toon graphics middle, toon graphics, middle
grade, graphics middle grade, graphics middle, gravity maze, math folder, game
libraries, math folder game, folder game libraries, prizewinning toon graphics,
prizewinning toon

27 : spanish edition, national geographic, national geographic readers,
geographic readers, diary wimpy, wimpy kid, diary wimpy kid, graphic novel, book
cd, big book, step reading, readers level, reader level, branches book,
nonfiction readers, scholastic reader, coloring book, scholastic reader level,
storybook cd, bk set

28 : standard shipping, height width, width length, height width length, norwood
commercial, norwood commercial furniture, commercial furniture, plastic stack,
stack stools, plastic stack stools, furniture noracso, noracso plastic stack,
width length assorted, assorted pack, furniture noracso plastic, length
assorted, stack stools height, length assorted pack, stools height, stools
height width

29 : nelson mandela, albert einstein, dr seuss, walt disney, abraham lincoln,
anne frank, true story, revere engineer, rosie revere, rosie revere engineer,
harriet tubman, george washington, underground railroad, rosa parks, amelia
earhart, jackie robinson, statue liberty, luther king, martin luther, martin
luther king
```

[ ]:
```
# map kmeans cluster -> final category name
merge_map = {
  0:"Books",10:"Books",11:"Books",20:"Books",27:"Books",29:"Books",
```

```
    1:"Stationery",2:"Stationery",9:"Stationery",14:"Stationery",18:
 ↪"Stationery",24:"Stationery",
    7:"Classroom_aid",8:"Classroom_aid",13:"Classroom_aid",28:"Classroom_aid",
    5:"STEM",16:"STEM",21:"STEM",26:"STEM",
    4:"Electronics",6:"Electronics",12:"Electronics",25:"Electronics",
    17:"Sports_Fitness",19:"Sports_Fitness",22:"Sports_Fitness",23:
 ↪"Sports_Fitness",
    15:"Food",
    3:"Subscriptions"
}

# apply
resources['resource_cluster'] = resources['kmeans_label'].map(merge_map)
```

[ ]:
```
# correcting mis-classified

books_index = resources[resources['cleaned_description'].str.contains('bk␣
 ↪set')].index
classroom_aid_index = resources[resources['cleaned_description'].str.
 ↪contains('bean bag|light|filters')].index
blanl_index = resources[resources['description']==''].index

resources.loc[books_index, 'resource_cluster'] = 'Books'
resources.loc[classroom_aid_index, 'resource_cluster'] = 'Classroom_aid'
resources.loc[blanl_index, 'resource_cluster'] = 'Other'
```

[ ]:
```
resources.head()
```

[ ]:
```
        id                                      description  quantity  \
0  p233245  LC652 - Lakeshore Double-Space Mobile Drying Rack         1
1  p069063        Bouncy Bands for Desks (Blue support pipes)         3
2  p069063  Cory Stories: A Kid's Book About Living With Adhd         1
3  p069063  Dixon Ticonderoga Wood-Cased #2 HB Pencils, Bo…        2
4  p069063  EDUCATIONAL INSIGHTS FLUORESCENT LIGHT FILTERS…        3

   unit_price  resource_cost  \
0      149.00         149.00
1       14.95          44.85
2        8.45           8.45
3       13.59          27.18
4       24.95          74.85

                           cleaned_description  kmeans_label  \
0       lc lakeshore doublespace mobile drying rack             7
1              bouncy bands desks blue support pipes            19
2                  cory stories kids book living adhd             3
3  dixon ticonderoga woodcased hb pencils box yellow             9
```

```
4  educational insights fluorescent light filters…           23

  resource_cluster
0    Classroom_aid
1   Sports_Fitness
2    Subscriptions
3       Stationery
4    Classroom_aid
```

### 1.3.2 project_title

[ ]:
```
projects.head()
```

[ ]:
```
        id                         teacher_id teacher_prefix school_state  \
0  p253737  c90749f5d961ff158d4b4d1e7dc665fc           Mrs.           IN
1  p258326  897464ce9ddc600bced1151f324dd63a            Mr.           FL
2  p182444  3465aaf82da834c0582ebd0ef8040ca0            Ms.           AZ
3  p246581  f3cb9bffbba169bef1a77b243e620b60           Mrs.           KY
4  p104768  be1f7507a41f8479dc06f047086a39ec           Mrs.           TX

  project_submitted_datetime project_grade_category  \
0        2016-12-05 13:43:00          Grades PreK-2
1        2016-10-25 09:22:00             Grades 6-8
2        2016-08-31 12:03:00             Grades 6-8
3        2016-10-06 21:16:00          Grades PreK-2
4        2016-07-11 01:10:00          Grades PreK-2

            project_subject_categories     project_subject_subcategories  \
0                  Literacy & Language                    ESL, Literacy
1    History & Civics, Health & Sports  Civics & Government, Team Sports
2                      Health & Sports    Health & Wellness, Team Sports
3  Literacy & Language, Math & Science            Literacy, Mathematics
4                       Math & Science                      Mathematics

                                    project_title  \
0   Educational Support for English Learners at Home
1              Wanted: Projector for Hungry Learners
2  Soccer Equipment for AWESOME Middle School Stu…
3                            Techie Kindergarteners
4                            Interactive Math Tools

                                  project_essay_1  \
0  My students are English learners that are work…
1  Our students arrive to our school eager to lea…
2  \r\n\"True champions aren't always the ones th…
3  I work at a unique school filled with both ESL…
4  Our second grade classroom next year will be m…
```

```
                                      project_essay_2 project_essay_3  \
0  \"The limits of your language are the limits o…
1  The projector we need for our school is very c…
2  The students on the campus come to school know…
3  My students live in high poverty conditions wi…
4  For many students, math is a subject that does…

  project_essay_4                           project_resource_summary  \
0                  My students need opportunities to practice beg…
1                  My students need a projector to help with view…
2                  My students need shine guards, athletic socks,…
3                  My students need to engage in Reading and Math…
4                  My students need hands on practice in mathemat…

   teacher_number_of_previously_posted_projects  project_is_approved
0                                             0                    0
1                                             7                    1
2                                             1                    0
3                                             4                    1
4                                             1                    1
```

[ ]:
```
project_title_df = projects[['id', 'project_title']]
project_title_df.head()
```

[ ]:
```
        id                                      project_title
0  p253737   Educational Support for English Learners at Home
1  p258326              Wanted: Projector for Hungry Learners
2  p182444  Soccer Equipment for AWESOME Middle School Stu…
3  p246581                              Techie Kindergarteners
4  p104768                              Interactive Math Tools
```

[ ]:
```
import re

def _syllables(word):
    w = re.sub(r'[^a-z]', '', word.lower())
    if not w: return 0
    groups = re.findall(r'[aeiou]+', w)
    cnt = len(groups)
    if w.endswith("e") and not w.endswith("le") and cnt > 1:
        cnt -= 1
    return max(1, cnt)

def readability_grade(title):
    text = (title or "").strip()
    text = re.sub(r'\\n|\\r|\\t|\\|\\a|\\b|\\f|\\v|\"', ' ', text) # removing␣
 ↪escape characters
```

```
    sentences = [s for s in re.split(r'[.!?]+', text) if s.strip()]
    s_cnt = max(1, len(sentences))
    words = re.findall(r"[A-Za-z0-9']+", text)
    w_cnt = max(1, len(words))
    syll = sum(_syllables(w) for w in words)
    fkgl = 0.39 * (w_cnt / s_cnt) + 11.8 * (syll / w_cnt) - 15.59
    return round(fkgl, 3)

project_title_df['title_readability_grade'] = project_title_df['project_title'].
    ↪apply(readability_grade)
```

[ ]:
```
_REQUEST_PAT = re.compile(
    r"\b(help|need|looking for|looking to|we␣
    ↪need|please|support|request|seeking|seek|donate|donation|want|would␣
    ↪like|asking for|looking|requesting)\b",
    flags=re.I
)

def is_request(title):
    t = (title or "").lower()
    # direct starts-with-verb heuristic (e.g., "Help us...", "Need...")
    if re.
    ↪match(r"^\s*(help|need|support|request|seeking|seek|looking|requesting)\b",␣
    ↪t):
        return 1
    return int(bool(_REQUEST_PAT.search(t)))

project_title_df['is_title_request'] = project_title_df['project_title'].
    ↪apply(is_request)
```

[ ]:
```
!pip install wordfreq --quiet
```

[ ]:
```
import statistics
from wordfreq import zipf_frequency

def creativity_score(title):
    text = (title or "").strip().lower()
    words = re.findall(r"[a-z0-9']+", text)
    if not words:
        return 0.0
    # zipf_frequency ~ 1..7 (higher = common). invert to get "rarity"
    freqs = [zipf_frequency(w, "en") for w in words]
    mean_zipf = statistics.mean(freqs)
    rare_score = max(0.0, 7.0 - mean_zipf)    # larger => rarer vocabulary
    # small punctuation bonus for stylistic flair
    punct_bonus = 1.0 if re.search(r"[!,:;\"'()-]", title) else 0.0
    score = rare_score * 0.85 + punct_bonus * 0.15
```

```
    return round(score, 3)

project_title_df['title_creativity_score'] = project_title_df['project_title'].
 ↪apply(creativity_score)
```

[ ]:
```
project_title_df.head()
```

[ ]:
```
         id                                    project_title  \
0  p253737   Educational Support for English Learners at Home
1  p258326              Wanted: Projector for Hungry Learners
2  p182444  Soccer Equipment for AWESOME Middle School Stu…
3  p246581                           Techie Kindergarteners
4  p104768                           Interactive Math Tools

   title_readability_grade  is_title_request  title_creativity_score
0                    10.74                 1                   1.297
1                     7.60                 0                   2.069
2                    10.74                 0                   1.405
3                    20.59                 0                   4.003
4                     9.18                 0                   2.238
```

[ ]:
```
import nltk
nltk.download('stopwords')

stop_words = nltk.corpus.stopwords.words('english')

def text_clean(text):
  text = text.lower()
  text = re.sub(r'\\n|\\r|\\t|\\|\\a|\\b|\\f|\\v', ' ', text) # removing escape␣
 ↪characters
  text = re.sub(r'[^a-z0-9 ]', ' ', text)
  text = re.sub(r'\s+', ' ', text).strip()
  text = [word for word in text.split() if word not in stop_words]
  return ' '.join(text)

project_title_df['cleaned_project_title'] = project_title_df['project_title'].
 ↪apply(text_clean)
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
```

[ ]:
```
# number of words in project title
project_title_df['cleaned_title_word_count'] =␣
 ↪project_title_df['cleaned_project_title'].apply(lambda x: len(x.split()))

# length of title
```

```
project_title_df['title_length'] = project_title_df['project_title'].
  ↪apply(lambda x: len(x))
```

[ ]:
```
project_title_df.head(5)
```

[ ]:
```
        id                                     project_title  \
0  p253737   Educational Support for English Learners at Home
1  p258326               Wanted: Projector for Hungry Learners
2  p182444  Soccer Equipment for AWESOME Middle School Stu…
3  p246581                             Techie Kindergarteners
4  p104768                             Interactive Math Tools

   title_readability_grade  is_title_request  title_creativity_score  \
0                    10.74                 1                   1.297
1                     7.60                 0                   2.069
2                    10.74                 0                   1.405
3                    20.59                 0                   4.003
4                     9.18                 0                   2.238

                       cleaned_project_title  cleaned_title_word_count  \
0       educational support english learners home                         5
1                 wanted projector hungry learners                         4
2  soccer equipment awesome middle school students                         6
3                          techie kindergarteners                         2
4                          interactive math tools                         3

   title_length
0            48
1            37
2            51
3            22
4            22
```

[ ]:
```
project_title_df.isna().sum()
```

[ ]:
```
id                          0
project_title               0
title_readability_grade     0
is_title_request            0
title_creativity_score      0
cleaned_project_title       0
cleaned_title_word_count    0
title_length                0
dtype: int64
```

### 1.3.3 project_essay

[ ]:
```
essay_cols = ["project_essay_1", "project_essay_2", "project_essay_3",␣
↪"project_essay_4"]

projects['project_essay'] = projects[essay_cols].agg(" ".join, axis=1)

projects.drop(columns=essay_cols, inplace=True)
```

[ ]:
```
projects.head()
```

[ ]:
```
        id                        teacher_id teacher_prefix school_state  \
0  p253737  c90749f5d961ff158d4b4d1e7dc665fc           Mrs.           IN
1  p258326  897464ce9ddc600bced1151f324dd63a            Mr.           FL
2  p182444  3465aaf82da834c0582ebd0ef8040ca0            Ms.           AZ
3  p246581  f3cb9bffbba169bef1a77b243e620b60           Mrs.           KY
4  p104768  be1f7507a41f8479dc06f047086a39ec           Mrs.           TX

  project_submitted_datetime project_grade_category  \
0        2016-12-05 13:43:00          Grades PreK-2
1        2016-10-25 09:22:00             Grades 6-8
2        2016-08-31 12:03:00             Grades 6-8
3        2016-10-06 21:16:00          Grades PreK-2
4        2016-07-11 01:10:00          Grades PreK-2

            project_subject_categories     project_subject_subcategories  \
0                  Literacy & Language                      ESL, Literacy
1    History & Civics, Health & Sports  Civics & Government, Team Sports
2                      Health & Sports    Health & Wellness, Team Sports
3  Literacy & Language, Math & Science              Literacy, Mathematics
4                       Math & Science                        Mathematics

                                      project_title  \
0   Educational Support for English Learners at Home
1               Wanted: Projector for Hungry Learners
2  Soccer Equipment for AWESOME Middle School Stu…
3                              Techie Kindergarteners
4                              Interactive Math Tools

                          project_resource_summary  \
0  My students need opportunities to practice beg…
1  My students need a projector to help with view…
2  My students need shine guards, athletic socks,…
3  My students need to engage in Reading and Math…
4  My students need hands on practice in mathemat…

   teacher_number_of_previously_posted_projects  project_is_approved  \
```

```
0                                                          0          0
1                                                          7          1
2                                                          1          0
3                                                          4          1
4                                                          1          1

                                         project_essay
0  My students are English learners that are work…
1  Our students arrive to our school eager to lea…
2  \r\n\"True champions aren't always the ones th…
3  I work at a unique school filled with both ESL…
4  Our second grade classroom next year will be m…
```

[ ]:
```python
projects_essay_df = projects[['id', 'project_essay']]
projects_essay_df.head()
```

[ ]:
```
        id                                     project_essay
0  p253737  My students are English learners that are work…
1  p258326  Our students arrive to our school eager to lea…
2  p182444  \r\n\"True champions aren't always the ones th…
3  p246581  I work at a unique school filled with both ESL…
4  p104768  Our second grade classroom next year will be m…
```

[ ]:
```python
import nltk
nltk.download('stopwords')

stop_words = nltk.corpus.stopwords.words('english')

def text_clean(text):
  text = text.lower()
  text = re.sub(r'\\n|\\r|\\t|\\|\\a|\\b|\\f|\\v', ' ', text) # removing escape␣
 ↪characters
  text = re.sub(r'[^a-z0-9 ]', ' ', text)
  text = re.sub(r'\s+', ' ', text).strip()
  text = [word for word in text.split() if word not in stop_words]
  return ' '.join(text)

projects_essay_df['cleaned_project_essay'] = projects_essay_df['project_essay'].
 ↪apply(text_clean)
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
```

[ ]:
```python
projects_essay_df.head()
```

[ ]:
```
        id                                     project_essay  \
0  p253737  My students are English learners that are work…
```

```
1  p258326  Our students arrive to our school eager to lea…
2  p182444  \r\n\"True champions aren't always the ones th…
3  p246581  I work at a unique school filled with both ESL…
4  p104768  Our second grade classroom next year will be m…

                              cleaned_project_essay
0  students english learners working english seco…
1  students arrive school eager learn polite gene…
2  true champions always ones win guts mia hamm q…
3  work unique school filled esl english second l…
4  second grade classroom next year made around 2…
```

[ ]:

```python
import re

def _syllables(word):
    w = re.sub(r'[^a-z]', '', word.lower())
    if not w: return 0
    groups = re.findall(r'[aeiou]+', w)
    cnt = len(groups)
    if w.endswith("e") and not w.endswith("le") and cnt > 1:
        cnt -= 1
    return max(1, cnt)

def readability_grade(title):
    text = (title or "").strip()
    text = re.sub(r'\\n|\\r|\\t|\\|\\a|\\b|\\f|\\v|\"', ' ', text) # removing␣
 ↪escape characters
    sentences = [s for s in re.split(r'[.!?]+', text) if s.strip()]
    s_cnt = max(1, len(sentences))
    words = re.findall(r"[A-Za-z0-9']+", text)
    w_cnt = max(1, len(words))
    syll = sum(_syllables(w) for w in words)
    fkgl = 0.39 * (w_cnt / s_cnt) + 11.8 * (syll / w_cnt) - 15.59
    return round(fkgl, 2)

projects_essay_df['essay_readability_grade'] =␣
 ↪projects_essay_df['project_essay'].apply(readability_grade)
```

[ ]:

```python
# number of words in project essay
projects_essay_df['cleaned_essay_word_count'] =␣
 ↪projects_essay_df['cleaned_project_essay'].apply(lambda x: len(x.split()))

# length of essay
projects_essay_df['essay_length'] = projects_essay_df['project_essay'].
 ↪apply(lambda x: len(x))

# sentence_count
```

```
projects_essay_df['essay_sentence_count'] = projects_essay_df['project_essay'].
↪apply(lambda x: len(re.split(r'[.!?]+\s*', x)))

# paragraph count
projects_essay_df['essay_paragraph_count'] = projects_essay_df['project_essay'].
↪apply(
    lambda x: len([p for p in re.split(r'(?:\\r\\n|\\r|\\n)+', str(x)) if p.
↪strip()])
)
```

[ ]:
```
projects_essay_df.head()
```

[ ]:
```
        id                                      project_essay  \
0  p253737  My students are English learners that are work…
1  p258326  Our students arrive to our school eager to lea…
2  p182444  \r\n\"True champions aren't always the ones th…
3  p246581  I work at a unique school filled with both ESL…
4  p104768  Our second grade classroom next year will be m…

                              cleaned_project_essay  essay_readability_grade  \
0  students english learners working english seco…                     9.11
1  students arrive school eager learn polite gene…                     9.16
2  true champions always ones win guts mia hamm q…                    11.20
3  work unique school filled esl english second l…                     9.07
4  second grade classroom next year made around 2…                     9.18

   cleaned_essay_word_count  essay_length  essay_sentence_count  \
0                       146          1632                    16
1                        96          1304                    13
2                       184          2096                    16
3                       108          1291                    13
4                       108          1326                    12

   essay_paragraph_count
0                      4
1                      3
2                      3
3                      3
4                      3
```

[ ]:
```
import re, html

def basic_clean(text):
    if not text:
        return ""
    text = html.unescape(str(text))    # fix &amp; etc.
    text = re.sub(r'(?:\\r\\n|\\r|\\n)+', ' ', text)
```

```
  text = re.sub(r'\s+', ' ', text)
  return text.strip()
```

[ ]:
```
!pip install vaderSentiment --quiet
```

```
                              0.0/126.0 kB
? eta -:--:--
                           126.0/126.0 kB
5.3 MB/s eta 0:00:00
```

[ ]:
```
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
analyzer = SentimentIntensityAnalyzer()

def sentiment_vader(text):
  text = basic_clean(text)
  return round(analyzer.polarity_scores(text)['compound'], 3)

projects_essay_df['essay_sentiment'] = projects_essay_df['project_essay'].
  ↪apply(sentiment_vader)
```

[ ]:
```
from textblob import TextBlob

def sentiment_subjectivity(text):
  text = basic_clean(text)
  return round(TextBlob(text).sentiment.subjectivity, 3)

projects_essay_df['essay_subjectivity'] = projects_essay_df['project_essay'].
  ↪apply(sentiment_subjectivity)
```

[ ]:
```
projects_essay_df.head()
```

[ ]:
```
        id                                      project_essay  \
0  p253737  My students are English learners that are work…
1  p258326  Our students arrive to our school eager to lea…
2  p182444  \r\n\"True champions aren't always the ones th…
3  p246581  I work at a unique school filled with both ESL…
4  p104768  Our second grade classroom next year will be m…

                               cleaned_project_essay  essay_readability_grade  \
0  students english learners working english seco…                     9.11
1  students arrive school eager learn polite gene…                     9.16
2  true champions always ones win guts mia hamm q…                    11.20
3  work unique school filled esl english second l…                     9.07
4  second grade classroom next year made around 2…                     9.18

   cleaned_essay_word_count  essay_length  essay_sentence_count  \
```

```
0                      146         1632                      16
1                       96         1304                      13
2                      184         2096                      16
3                      108         1291                      13
4                      108         1326                      12

   essay_paragraph_count  essay_sentiment  essay_subjectivity
0                      4            0.970               0.282
1                      3            0.931               0.412
2                      3            0.997               0.486
3                      3            0.994               0.434
4                      3            0.919               0.558
```

## 1.4 Feature Engineering

[ ]:
```python
projects.head()
```

[ ]:
```
        id                        teacher_id teacher_prefix school_state  \
0  p253737  c90749f5d961ff158d4b4d1e7dc665fc           Mrs.           IN
1  p258326  897464ce9ddc600bced1151f324dd63a            Mr.           FL
2  p182444  3465aaf82da834c0582ebd0ef8040ca0            Ms.           AZ
3  p246581  f3cb9bffbba169bef1a77b243e620b60           Mrs.           KY
4  p104768  be1f7507a41f8479dc06f047086a39ec           Mrs.           TX

  project_submitted_datetime project_grade_category  \
0        2016-12-05 13:43:00          Grades PreK-2
1        2016-10-25 09:22:00             Grades 6-8
2        2016-08-31 12:03:00             Grades 6-8
3        2016-10-06 21:16:00          Grades PreK-2
4        2016-07-11 01:10:00          Grades PreK-2

            project_subject_categories     project_subject_subcategories  \
0                  Literacy & Language                     ESL, Literacy
1    History & Civics, Health & Sports  Civics & Government, Team Sports
2                      Health & Sports    Health & Wellness, Team Sports
3  Literacy & Language, Math & Science            Literacy, Mathematics
4                       Math & Science                       Mathematics

                                     project_title  \
0   Educational Support for English Learners at Home
1              Wanted: Projector for Hungry Learners
2  Soccer Equipment for AWESOME Middle School Stu…
3                             Techie Kindergarteners
4                             Interactive Math Tools

                          project_resource_summary  \
0  My students need opportunities to practice beg…
```

```
1  My students need a projector to help with view…
2  My students need shine guards, athletic socks,…
3  My students need to engage in Reading and Math…
4  My students need hands on practice in mathemat…

   teacher_number_of_previously_posted_projects  project_is_approved  \
0                                             0                    0
1                                             7                    1
2                                             1                    0
3                                             4                    1
4                                             1                    1

                                     project_essay
0  My students are English learners that are work…
1  Our students arrive to our school eager to lea…
2  \r\n\"True champions aren't always the ones th…
3  I work at a unique school filled with both ESL…
4  Our second grade classroom next year will be m…
```

[ ]:
```
resources.head()
```

[ ]:
```
        id                                        description  quantity  \
0  p233245  LC652 - Lakeshore Double-Space Mobile Drying Rack         1
1  p069063        Bouncy Bands for Desks (Blue support pipes)         3
2  p069063  Cory Stories: A Kid's Book About Living With Adhd         1
3  p069063  Dixon Ticonderoga Wood-Cased #2 HB Pencils, Bo…         2
4  p069063  EDUCATIONAL INSIGHTS FLUORESCENT LIGHT FILTERS…         3

   unit_price  resource_cost  \
0      149.00         149.00
1       14.95          44.85
2        8.45           8.45
3       13.59          27.18
4       24.95          74.85

                              cleaned_description  kmeans_label  \
0      lc lakeshore doublespace mobile drying rack             7
1             bouncy bands desks blue support pipes            19
2                 cory stories kids book living adhd             3
3  dixon ticonderoga woodcased hb pencils box yellow             9
4  educational insights fluorescent light filters…           23

  resource_cluster
0    Classroom_aid
1   Sports_Fitness
2    Subscriptions
3       Stationery
```

```
4    Classroom_aid
```

[ ]:
```
resources_pivot = resources.pivot_table(
    index='id',
    columns='resource_cluster',
    values='quantity',
    aggfunc='sum',
    fill_value=0
)

resources_pivot.columns.name = None
resources_pivot.reset_index(inplace=True)
resources_pivot = resources_pivot.sort_values(by='id').reset_index(drop=True)
resources_pivot.head()
```

[ ]:
```
        id  Books  Classroom_aid  Electronics  Food  Other  STEM  \
0  p000001      0              0            0     0      0     0
1  p000002      4              4            7     0      0     0
2  p000003      0              0            0     0      0     0
3  p000004     95              1            0     0      0     0
4  p000005      0              0            7     0      0     1

   Sports_Fitness  Stationery  Subscriptions
0               7           0              0
1               3           3              0
2               0           2              2
3               0           0              2
4               0           0              0
```

[ ]:
```
resources_cost_agg = resources.groupby("id", as_index=False)['resource_cost'].
 ↪sum().sort_values(by='id').reset_index(drop=True)
resources_cost_agg.head()
```

[ ]:
```
        id  resource_cost
0  p000001         833.63
1  p000002         630.28
2  p000003         298.97
3  p000004        1126.22
4  p000005         702.31
```

[ ]:
```
resources_pivot['total_resource_cost'] = resources_cost_agg['resource_cost'].
 ↪copy()
resources_pivot.head()
```

[ ]:
```
        id  Books  Classroom_aid  Electronics  Food  Other  STEM  \
0  p000001      0              0            0     0      0     0
1  p000002      4              4            7     0      0     0
```

```
2  p000003      0              0            0      0       0      0
3  p000004     95              1            0      0       0      0
4  p000005      0              0            7      0       0      1

   Sports_Fitness  Stationery  Subscriptions  total_resource_cost
0               7           0              0               833.63
1               3           3              0               630.28
2               0           2              2               298.97
3               0           0              2              1126.22
4               0           0              0               702.31
```

[ ]:
```python
df = pd.merge(projects, resources_pivot, on='id', how='left').
 ↪sort_values(by='project_submitted_datetime').reset_index(drop=True)
df.head()
```

[ ]:
```
        id                        teacher_id teacher_prefix school_state  \
0  p205479  2bf07ba08945e5d8b2a3f269b2b3cfe5           Mrs.           CA
1  p043609  3f60494c61921b3b43ab61bdde2904df            Ms.           UT
2  p189804  4a97f3a390bfe21b99cf5e2b81981c73           Mrs.           CA
3  p234804  cbc0e38f522143b86d372f8b43d4cff3           Mrs.           GA
4  p137682  06f6e62e17de34fcf81020c77549e1d5           Mrs.           WA

  project_submitted_datetime project_grade_category  \
0        2016-04-27 00:27:00          Grades PreK-2
1        2016-04-27 00:31:00             Grades 3-5
2        2016-04-27 00:46:00          Grades PreK-2
3        2016-04-27 00:53:00          Grades PreK-2
4        2016-04-27 01:05:00             Grades 3-5

  project_subject_categories            project_subject_subcategories  \
0             Math & Science  Applied Sciences, Health & Life Science
1              Special Needs                            Special Needs
2        Literacy & Language                                 Literacy
3           Applied Learning                        Early Development
4        Literacy & Language                                 Literacy

                                   project_title  \
0    Engineering STEAM into the Primary Classroom
1                          Sensory Tools for Focus
2  Mobile Learning with a Mobile Listening Center
3          Flexible Seating for Flexible Learning
4          Going Deep: The Art of Inner Thinking!

                           project_resource_summary  …  Books  \
0  My students need STEM kits to learn critical s…  …      0
1  My students need Boogie Boards for quiet senso…  …      1
2  My students need a mobile listening center to …  …      0
```

```
3  My students need flexible seating in the class…  …      0
4  My students need copies of the New York Times …  …     14

   Classroom_aid Electronics  Food  Other  STEM  Sports_Fitness  Stationery  \
0              0           0     0      0     3               0           1
1              1           3     0      0     2               0           1
2              0           1     0      0     0               0           0
3              5           0     0      0     0               4           0
4              0           0     0      0     0               0           0

   Subscriptions  total_resource_cost
0              0               725.05
1              0               213.03
2              0               329.00
3              0               774.92
4              0               124.18

[5 rows x 23 columns]
```

[ ]:

```
# Time-based features
df["project_submitted_date"] = df["project_submitted_datetime"].dt.date
df["project_submission_year"] = df["project_submitted_datetime"].dt.year
df["project_submission_month"] = df["project_submitted_datetime"].dt.
↪month_name()
df["project_submission_day"] = df["project_submitted_datetime"].dt.day_name()
df["project_submission_hour"] = df["project_submitted_datetime"].dt.hour
```

[ ]:

```
df.drop(columns=['project_submitted_datetime', 'project_resource_summary'],␣
↪inplace=True)
df.head()
```

[ ]:

```
        id                        teacher_id teacher_prefix school_state  \
0  p205479  2bf07ba08945e5d8b2a3f269b2b3cfe5           Mrs.           CA
1  p043609  3f60494c61921b3b43ab61bdde2904df            Ms.           UT
2  p189804  4a97f3a390bfe21b99cf5e2b81981c73           Mrs.           CA
3  p234804  cbc0e38f522143b86d372f8b43d4cff3           Mrs.           GA
4  p137682  06f6e62e17de34fcf81020c77549e1d5           Mrs.           WA

  project_grade_category project_subject_categories  \
0          Grades PreK-2             Math & Science
1             Grades 3-5              Special Needs
2          Grades PreK-2        Literacy & Language
3          Grades PreK-2           Applied Learning
4             Grades 3-5        Literacy & Language

             project_subject_subcategories  \
0  Applied Sciences, Health & Life Science
```

```
1                        Special Needs
2                             Literacy
3                    Early Development
4                             Literacy

                                 project_title  \
0   Engineering STEAM into the Primary Classroom
1                      Sensory Tools for Focus
2  Mobile Learning with a Mobile Listening Center
3          Flexible Seating for Flexible Learning
4          Going Deep: The Art of Inner Thinking!

   teacher_number_of_previously_posted_projects  project_is_approved  …  \
0                                            53                    1  …
1                                             4                    1  …
2                                            10                    1  …
3                                             2                    1  …
4                                             2                    1  …

  STEM  Sports_Fitness  Stationery  Subscriptions  total_resource_cost  \
0    3               0           1              0               725.05
1    2               0           1              0               213.03
2    0               0           0              0               329.00
3    0               4           0              0               774.92
4    0               0           0              0               124.18

   project_submitted_date  project_submission_year  project_submission_month  \
0              2016-04-27                     2016                     April
1              2016-04-27                     2016                     April
2              2016-04-27                     2016                     April
3              2016-04-27                     2016                     April
4              2016-04-27                     2016                     April

   project_submission_day  project_submission_hour
0               Wednesday                        0
1               Wednesday                        0
2               Wednesday                        0
3               Wednesday                        0
4               Wednesday                        1

[5 rows x 26 columns]
```

[ ]:
```
column_analysis(df)
```

[ ]:
```
                                         column    dtype  null_count  \
0                                            id   object           0
1                                    teacher_id   object           0
```

| | | | |
|---|---|---|---|
| 2 | teacher_prefix | object | 0 |
| 3 | school_state | object | 0 |
| 4 | project_grade_category | object | 0 |
| 5 | project_subject_categories | object | 0 |
| 6 | project_subject_subcategories | object | 0 |
| 7 | project_title | object | 0 |
| 8 | teacher_number_of_previously_posted_projects | int64 | 0 |
| 9 | project_is_approved | int64 | 0 |
| 10 | project_essay | object | 0 |
| 11 | Books | int64 | 0 |
| 12 | Classroom_aid | int64 | 0 |
| 13 | Electronics | int64 | 0 |
| 14 | Food | int64 | 0 |
| 15 | Other | int64 | 0 |
| 16 | STEM | int64 | 0 |
| 17 | Sports_Fitness | int64 | 0 |
| 18 | Stationery | int64 | 0 |
| 19 | Subscriptions | int64 | 0 |
| 20 | total_resource_cost | float64 | 0 |
| 21 | project_submitted_date | object | 0 |
| 22 | project_submission_year | int32 | 0 |
| 23 | project_submission_month | object | 0 |
| 24 | project_submission_day | object | 0 |
| 25 | project_submission_hour | int32 | 0 |

| | nunique | sample_values |
|---|---|---|
| 0 | 109248 | p035880\| p074444\| p248443\| p101684\| p240101 |
| 1 | 72168 | 463b6eb7743771c21b4f62d70e1b8b99\| 4f9171805c2f… |
| 2 | 5 | Mrs.\| Mrs.\| Ms.\| Mrs.\| Mrs. |
| 3 | 51 | IN\| CA\| MO\| KS\| IL |
| 4 | 4 | Grades PreK-2\| Grades 3-5\| Grades PreK-2\| Grad… |
| 5 | 51 | Literacy & Language\| Literacy & Language, Math… |
| 6 | 401 | Extracurricular, Literature & Writing\| Applied… |
| 7 | 100850 | Student Desks and Chairs are LONG Past Retirem… |
| 8 | 374 | 9\| 10\| 1\| 44\| 39 |
| 9 | 2 | 1\| 1\| 1\| 1\| 1 |
| 10 | 108986 | My students are an eager bunch of learners!! T… |
| 11 | 230 | 0\| 0\| 0\| 3\| 0 |
| 12 | 144 | 11\| 0\| 0\| 0\| 0 |
| 13 | 103 | 0\| 2\| 0\| 12\| 0 |
| 14 | 83 | 1\| 0\| 0\| 0\| 0 |
| 15 | 7 | 0\| 0\| 0\| 0\| 0 |
| 16 | 91 | 0\| 0\| 0\| 3\| 0 |
| 17 | 132 | 0\| 6\| 0\| 0\| 0 |
| 18 | 253 | 0\| 0\| 0\| 0\| 0 |
| 19 | 135 | 1\| 36\| 0\| 0\| 0 |
| 20 | 59066 | 1821.97\| 799.5\| 175.42\| 368.88\| 1041.27 |

```
21       369  2016-11-09| 2017-02-16| 2016-08-15| 2016-08-02…
22         2                     2016| 2017| 2016| 2016| 2016
23        12            June| June| September| November| March
24         7          Sunday| Saturday| Sunday| Sunday| Friday
25        24                                 10| 18| 18| 2| 10
```

[ ]:
```
df.describe().T
```

[ ]:
```
                                                count         mean  \
teacher_number_of_previously_posted_projects  109248.0    11.153165
project_is_approved                           109248.0     0.848583
Books                                         109248.0     4.085521
Classroom_aid                                 109248.0     1.813187
Electronics                                   109248.0     2.109375
Food                                          109248.0     0.340537
Other                                         109248.0     0.001108
STEM                                          109248.0     1.250302
Sports_Fitness                                109248.0     2.282477
Stationery                                    109248.0     3.804234
Subscriptions                                 109248.0     1.278870
total_resource_cost                           109248.0   545.580439
project_submission_year                       109248.0  2016.277186
project_submission_hour                       109248.0    14.459578

                                                     std     min        25%  \
teacher_number_of_previously_posted_projects   27.777154     0.0     0.0000
project_is_approved                             0.358456     0.0     1.0000
Books                                          15.906993     0.0     0.0000
Classroom_aid                                   7.041146     0.0     0.0000
Electronics                                     6.310040     0.0     0.0000
Food                                            2.807968     0.0     0.0000
Other                                           0.052304     0.0     0.0000
STEM                                            4.559016     0.0     0.0000
Sports_Fitness                                  7.519612     0.0     0.0000
Stationery                                     15.021971     0.0     0.0000
Subscriptions                                   7.859117     0.0     0.0000
total_resource_cost                           546.829779   100.0   245.9175
project_submission_year                         0.447611  2016.0  2016.0000
project_submission_hour                         5.761503     0.0    11.0000

                                              50%      75%     max
teacher_number_of_previously_posted_projects  2.0   9.0000  451.00
project_is_approved                           1.0   1.0000    1.00
Books                                         0.0   0.0000  865.00
Classroom_aid                                 0.0   1.0000  410.00
Electronics                                   0.0   2.0000  400.00
Food                                          0.0   0.0000  175.00
```

```
Other                                        0.0     0.0000     11.00
STEM                                         0.0     1.0000    576.00
Sports_Fitness                               0.0     1.0000    400.00
Stationery                                   0.0     2.0000    900.00
Subscriptions                                0.0     0.0000    351.00
total_resource_cost                        397.0   691.5525  13543.82
project_submission_year                   2016.0  2017.0000   2017.00
project_submission_hour                     15.0    19.0000     23.00
```

[ ]:
```python
df.describe(include='object')
```

[ ]:
```
                 id                        teacher_id teacher_prefix school_state  \
count        109248                            109248         109248       109248
unique       109248                             72168              5           51
top         p149431  fa2f220b537e8653fb48878ebb38044d           Mrs.           CA
freq              1                                44          57272        15388

       project_grade_category project_subject_categories  \
count                  109248                     109248
unique                      4                         51
top             Grades PreK-2         Literacy & Language
freq                    44225                      23655

       project_subject_subcategories     project_title  \
count                         109248            109248
unique                           401            100850
top                         Literacy  Flexible Seating
freq                            9486               234

                                          project_essay  \
count                                            109248
unique                                           108986
top     Hello, I teach a great group of students who a…
freq                                                  5

       project_submitted_date project_submission_month project_submission_day
count                  109248                   109248                 109248
unique                    369                       12                      7
top                2016-09-01                   August              Wednesday
freq                     2601                    19980                  19219
```

- **High approval rate:** ~85% projects are approved → dataset is **highly imbalanced** toward approvals.
- **Teacher experience matters:** Median previous projects = **2**, but long tail up to **451** → a few highly active teachers dominate submissions.
- **First-time teachers are common:** 25% teachers have **0** prior projects → strong scope to compare approval by experience.

- **Resource requests are sparse:** Most category counts have **median = 0**, meaning projects usually focus on **1–2 resource types only**.
- **Books & Stationery dominate:** Highest average counts and extreme max values → core classroom needs drive requests.
- **STEM & Electronics are moderate:** Present but not dominant → specialized projects form a smaller share.
- **Food & "Other" are negligible:** Very low means and medians → limited impact on approval modeling.
- **Cost is right-skewed:** Median  **USD 397**, max > **USD 13k** → log transformation or binning is necessary.
- **Typical project cost range:** 50% of projects lie between **USD 246 – USD 692**.
- **Temporal concentration:** Submissions mostly in **2016–2017**, limiting long-term trend analysis.
- **Peak submission time:** Median hour = **3 PM**, with most submissions between **11 AM – 7 PM** → daytime behavior.
- **High teacher repeat behavior:** 72k teachers for 109k projects → many teachers submit **multiple proposals**.
- **Prefix skew:** *Mrs.* dominates (~52%) → teacher_prefix is **imbalanced**, low but usable signal.
- **Geographic concentration: California (CA)** has the highest submissions → strong state-level skew.
- **Grade imbalance: PreK–2** dominates (~40%) → early education projects are most common.
- **Subject dominance: Literacy & Language** is the top category → core academic needs drive demand.
- **High subcategory granularity:** 401 subcategories → **high-cardinality**, needs grouping/encoding.
- **Titles are mostly unique:** ~100k unique titles → TF-IDF/embeddings better than frequency-based features.
- **Essays are almost always unique:** Minimal duplication → strong signal but **high dimensional**.
- **Temporal clustering:** Only **369 unique dates** → submissions are bursty, not continuous.
- **Seasonality: August** is peak month → aligns with school-year start.
- **Weekday bias: Wednesday** highest → school-hour submission behavior.

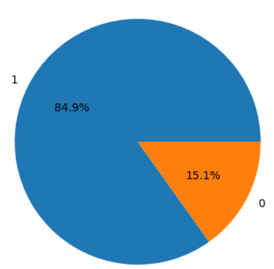
### 1.5 Exploratory Data Analysis

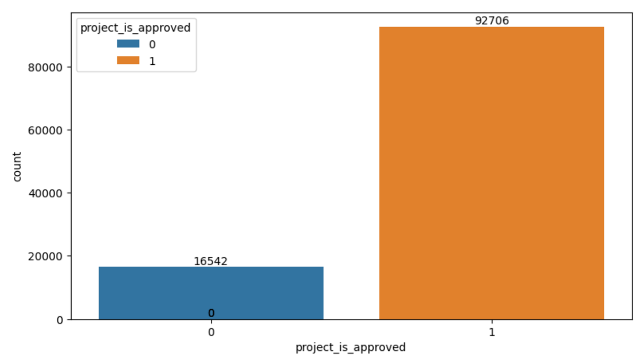
[ ]:
```
# import numpy as np
# import pandas as pd
# import matplotlib.pyplot as plt
# import seaborn as sns
# import warnings
# warnings.filterwarnings('ignore')

# !gdown 15_ylYp27G-tjpXmusKQec7R9saX-_YqM    # resources_preprocessed.csv
# !gdown 1d-nscAgfP4nyFWD228nF9SPdePrQFPTT    # projects_preprocessed.csv
# !gdown 12utMaStw_pLLmOu3kpYJaw5enOTOvuwC    # project_title.csv
```

```
# !gdown 1VO4CYzGKLmVElCMHp96aUdZhvJ5-CItf    # projects_essay.csv
# !gdown 1SbtSutPBDlhQoOHcbKNareXTxcA63e07    # merged.csv


# resources = pd.read_csv('/content/resources_preprocessed.csv')
# projects = pd.read_csv('/content/projects_preprocessed.csv')
# project_title_df = pd.read_csv('/content/project_title.csv')
# projects_essay_df = pd.read_csv('/content/projects_essay.csv')
# df = pd.read_csv('/content/merged.csv')

# resources.fillna('', inplace=True)
# projects.fillna('', inplace=True)
# project_title_df.fillna('', inplace=True)
# projects_essay_df.fillna('', inplace=True)
# df.fillna('', inplace=True)

# projects["project_submitted_datetime"] = pd.to_datetime(
#     projects["project_submitted_datetime"], format="%Y-%m-%d %H:%M:%S"
# )
```

#### 1.5.1 Approval Ratio

[ ]:
```
plt.figure(figsize=(20, 5))
plt.subplot(1, 2, 1)
plt.pie(df['project_is_approved'].value_counts(),
        labels=df['project_is_approved'].value_counts().index,
        autopct='%1.1f%%')

plt.subplot(1, 2, 2)
g = sns.countplot(data=df, x='project_is_approved', hue='project_is_approved')
for p in g.patches:
    g.text(p.get_x() + p.get_width() / 2, p.get_height(), int(p.get_height()),␣
↪ha='center', va='bottom')
```



- **High approval rate:** ~85% projects are approved → dataset is **highly imbalanced** toward approvals.

### 1.5.2 Hypothesis Testing Template

[ ]:
```python
from scipy.stats import chi2_contingency

def chisquare_test(df, columns, target_col, table=True):
  results = []

  if type(columns) == str:
    columns = [columns]

  for col in columns:

    # contingency table
    contingency_table = pd.crosstab(df[col], df[target_col])
    if table:
      print(contingency_table, '\n')

    # Chi-square test
    chi2, p, dof, expected = chi2_contingency(contingency_table)

    # Cramér's V calculation
    n = contingency_table.sum().sum()
    k = min(contingency_table.shape) - 1  # min(#rows, #cols) - 1
    cramers_v = np.sqrt(chi2 / (n * k))

    # Interpretation - Practical effect
    if cramers_v < 0.10:
      effect = "Negligible"
    elif cramers_v < 0.30:
      effect = "Weak"
    elif cramers_v < 0.50:
      effect = "Moderate"
    else:
      effect = "Strong"

    # statistical interpretation
    if p<0.05:
      res = 1 #'Reject null hypothesis' (H1: dependent)
    else:
      res =  0 #'Fail to reject null hypothesis' (H0: independent)

    dependent_feature = target_col+'_dependent_on_category'

    results.append({
```

```
      'category': col,
      'p_value': p,
      'chi2_stat': chi2,
       dependent_feature: res,
      'cramers_v': cramers_v,
      'effect': effect
    })

  return pd.DataFrame(results)
```

[ ]:
```
# ttest
from scipy.stats import ttest_ind, levene

def ttest(df, num_col, cat_col, table=True):
  results = []

  a,b = df[cat_col].unique()

  if table:
    print(df.groupby(cat_col)[num_col].mean().reset_index())

  group1 = df[df[cat_col] == a][num_col]
  group2 = df[df[cat_col] == b][num_col]

  levene_stat, levene_p = levene(group1, group2)

  if levene_p < 0.05:
    var = False  # unequal variance
  else:
    var = True   # equal variance

  ttest_stat, ttest_p = ttest_ind(group1, group2,
                                  equal_var=var,
                                  alternative='two-sided')

  s1, s2 = group1.std(), group2.std()
  n1, n2 = len(group1), len(group2)

  s_pooled = np.sqrt(((n1-1)*s1**2 + (n2-1)*s2**2) / (n1+n2-2))
  cohens_d = (group1.mean() - group2.mean()) / s_pooled

  d = abs(cohens_d)
  if d < 0.10:
      effect = "Negligible"
  elif d < 0.30:
      effect = "Weak"
  elif d < 0.50:
```

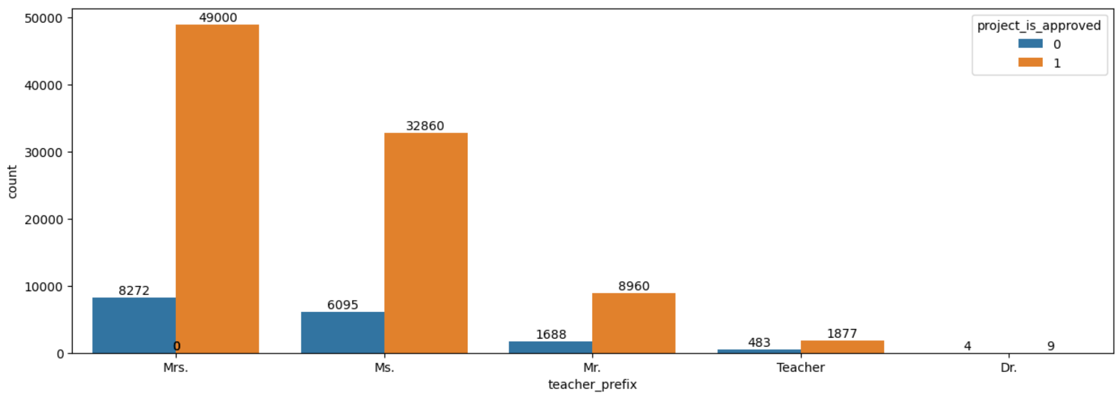
```
        effect = "Moderate"
    else:
        effect = "Strong"

    if ttest_p < 0.05:
      res = 'different' #'Reject null hypothesis' (H1)
    else:
      res = 'same' #'Fail to reject null hypothesis' (H0)

    results.append({
        'numerical_column': num_col,
        'categorical_column': cat_col,
        'means': res,
        't_stat': ttest_stat,
        'p_value': ttest_p,
        'variances': 'equal' if var else 'unequal',
        'levene_stat': levene_stat,
        'levene_p': levene_p,
        'cohens_d': cohens_d,
        'effect': effect
      })

    return pd.DataFrame(results)
```

[ ]:
```
# pearsonr correlation
from scipy.stats import pearsonr, spearmanr

def pearson_corr(df, col1, col2):
  results=[]
  r, p = pearsonr(df[col1], df[col2], alternative='two-sided')
  if p<0.05:
    res='Related' #'Reject null hypothesis' (H1)
  else:
    res='Not Related' #'Fail to reject null hypothesis' (H0)

  abs_r = abs(r)
  if abs_r < 0.10:
    effect = "Negligible"
  elif abs_r < 0.30:
    effect = "Weak"
  elif abs_r < 0.50:
    effect = "Moderate"
  else:
    effect = "Strong"

  results.append({
      'column1': col1,
```

```
            'column2': col2,
            'correlation': r,
            'p_value': p,
            'relation': res,
            'effect': effect
        })

    return pd.DataFrame(results)
```

### 1.5.3 Teacher Analysis

[ ]:
```
plt.figure(figsize=(15, 5))
g = sns.countplot(data=df, x='teacher_prefix', hue='project_is_approved')
for p in g.patches:
    g.text(p.get_x() + p.get_width() / 2, p.get_height(), int(p.get_height()),␣
 ↪ha='center', va='bottom')
plt.show()
```

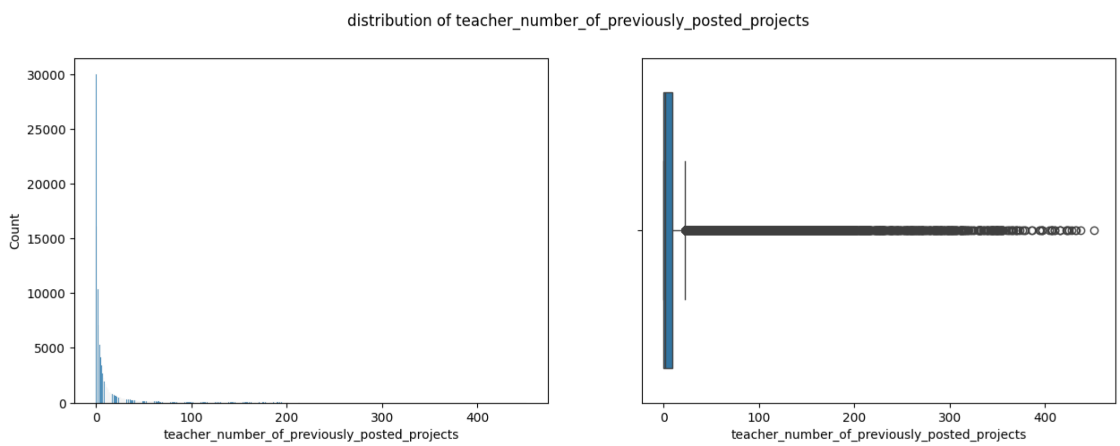



[ ]:
```
df['teacher_id'].value_counts()
```

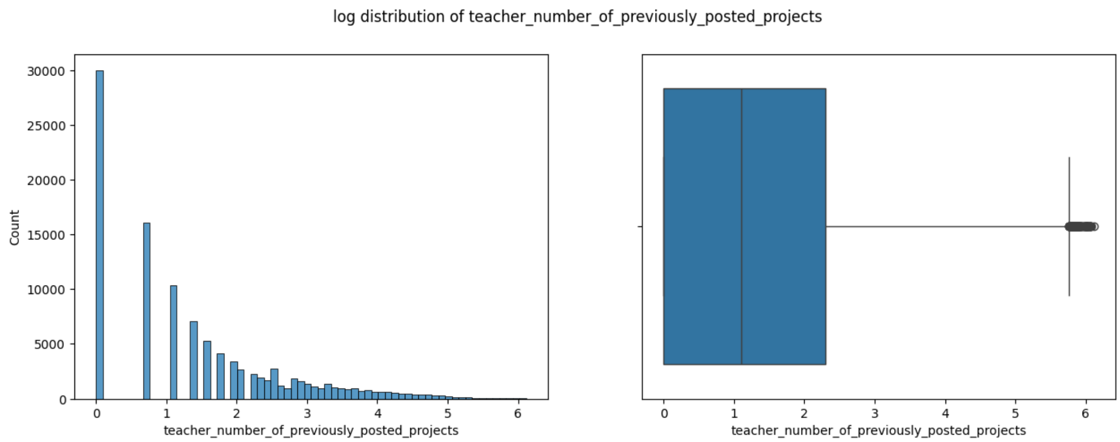
[ ]:
```
teacher_id
fa2f220b537e8653fb48878ebb38044d    44
1f64dcec848be8e95c4482cc845706b2    42
df8a4b7ad173b57f7ac52e447cc24043    42
7b17c95da53e3d1f011f84232ad01238    34
ae67d8bbc64ec3bf7fd2db1297721160    33
                                    ..
304cc00e13df870fc1cddf61daef7b7d     1
8a81a0f39b5ab1b0325425e6e603466c     1
980fad5115c9cd1acabf7372cffb0894     1
02847fc657be0b5268bc80e2e79917db     1
cf5c9c6f50db79eccd01ca945945973d     1
```

```
Name: count, Length: 72168, dtype: int64
```

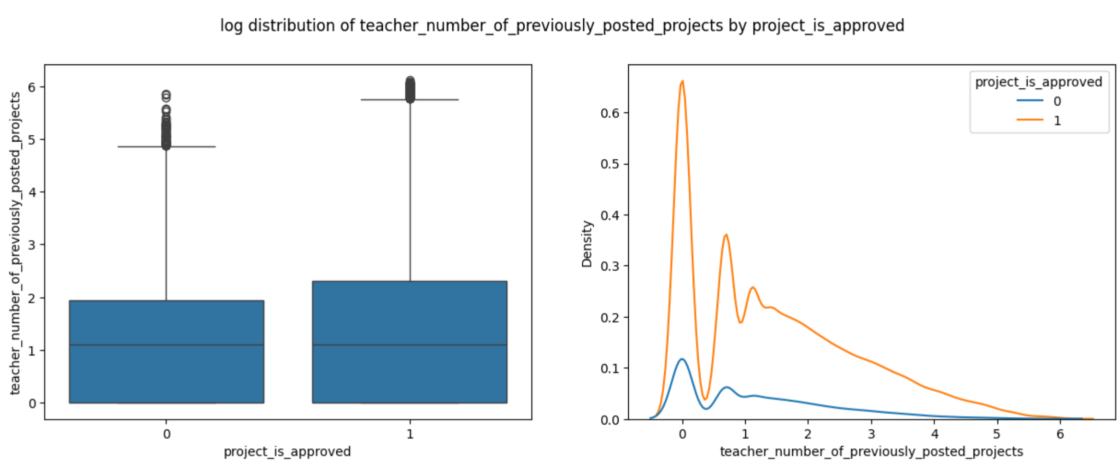
[ ]:
```
fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(15, 5))
sns.histplot(data=df, x='teacher_number_of_previously_posted_projects',␣
 ↪ax=ax[0])
sns.boxplot(data=df, x='teacher_number_of_previously_posted_projects', ax=ax[1])
plt.suptitle('distribution of teacher_number_of_previously_posted_projects')
plt.show()
```




[ ]:
```
log_teacher_exp_df = pd.DataFrame({
    'teacher_number_of_previously_posted_projects': np.
 ↪log1p(df['teacher_number_of_previously_posted_projects']),
    'project_is_approved': df['project_is_approved'].astype('category')
})

fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(15, 5))
sns.histplot(data=log_teacher_exp_df,␣
 ↪x='teacher_number_of_previously_posted_projects', ax=ax[0])
sns.boxplot(data=log_teacher_exp_df,␣
 ↪x='teacher_number_of_previously_posted_projects', ax=ax[1])
plt.suptitle('log distribution of teacher_number_of_previously_posted_projects')
plt.show()
```




[ ]:
```
fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(15, 5))
sns.boxplot(data=log_teacher_exp_df, y='teacher_number_of_previously_posted_projects', x='project_is_approved', ax=ax[0])
sns.kdeplot(data=log_teacher_exp_df, x='teacher_number_of_previously_posted_projects', hue='project_is_approved', ax=ax[1])
plt.suptitle('log distribution of teacher_number_of_previously_posted_projects by project_is_approved')
plt.show()
```




[ ]:
```
ttest(df=log_teacher_exp_df,
      num_col='teacher_number_of_previously_posted_projects',
      cat_col='project_is_approved')
```

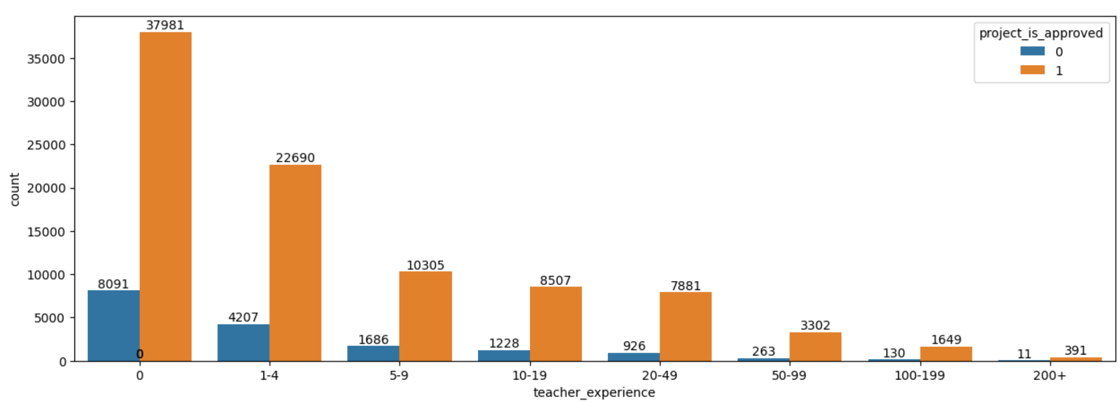
```
project_is_approved  teacher_number_of_previously_posted_projects
```

```
0                   0                                      1.188520
1                   1                                      1.484312
```

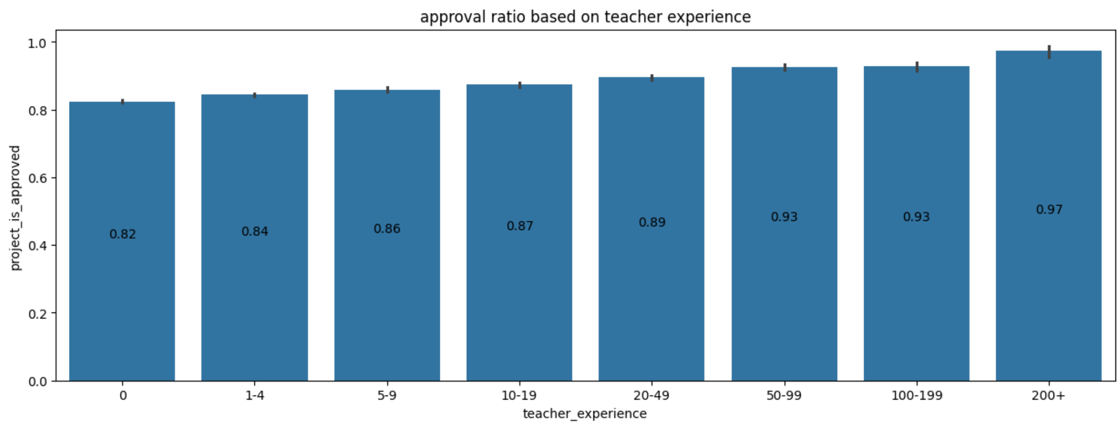
[ ]:
```
                               numerical_column   categorical_column  \
0  teacher_number_of_previously_posted_projects  project_is_approved

       means     t_stat        p_value variances  levene_stat      levene_p  \
0  different  29.395591  9.482921e-187   unequal   447.207909  4.622376e-99

   cohens_d effect
0   0.22557   Weak
```

[ ]:
```python
bins = [0, 1, 5, 10, 20, 50, 100, 200, np.inf]
labels = [
    '0',         # First project
    '1-4',       # New
    '5-9',       # Beginner+
    '10-19',     # Growing
    '20-49',     # Seasoned
    '50-99',     # Highly active
    '100-199',   # Veteran
    '200+'       # Exceptional long-term poster
]

df['teacher_experience'] = pd.
↪cut(df['teacher_number_of_previously_posted_projects'],
                                 bins=bins, labels=labels, include_lowest=True)
```

[ ]:
```python
plt.figure(figsize=(15, 5))
g = sns.countplot(data=df, x='teacher_experience', hue='project_is_approved')
for p in g.patches:
    g.text(p.get_x() + p.get_width() / 2, p.get_height(), int(p.get_height()),␣
↪ha='center', va='bottom')
plt.show()
```



[ ]:
```
# approval ratio based on teacher experience
plt.figure(figsize=(15, 5))
g = sns.barplot(data=df, x='teacher_experience', y='project_is_approved')
for p in g.patches:
    g.text(p.get_x() + p.get_width() / 2, p.get_height()/2, p.get_height().
 ↪round(2), ha='center', va='bottom')
plt.title('approval ratio based on teacher experience')
plt.show()
```




[ ]:
```
df.groupby('teacher_experience')['project_is_approved'].mean()
```

[ ]:
```
teacher_experience
0          0.824384
1-4        0.843589
5-9        0.859395
10-19      0.873857
20-49      0.894856
50-99      0.926227
100-199    0.926925
200+       0.972637
Name: project_is_approved, dtype: float64
```

[ ]:
```
chisquare_test(df, columns=['teacher_id', 'teacher_prefix',␣
 ↪'teacher_experience'], target_col='project_is_approved')
```

```
project_is_approved               0  1
teacher_id
00000f7264c27ba6fea0c837ed6aa0aa  0  1
00002d44003ed46b066607c5455a999a  0  2
00006084c3d92d904a22e0a70f5c119a  0  2
0000a9af8b6b9cc9e41f53322a8b8cf1  0  1
```

```
0000d4777d14b33a1406dd6c9019fe89  0  1
…                                 .. ..
fffb368120440683f9371494de10f308  1  0
fffe543adc962547e0666e53ae7c4773  0  2
ffff80baec08450113ceb12f068d9cb4  0  1
ffff8bee61b72c484b10e43aa9e35bc9  0  2
ffff8e040521f62207881376ecc964d5  0  1

[72168 rows x 2 columns]

project_is_approved     0      1
teacher_prefix
Dr.                     4      9
Mr.                  1688   8960
Mrs.                 8272  49000
Ms.                  6095  32860
Teacher               483   1877

project_is_approved     0      1
teacher_experience
0                    8091  37981
1-4                  4207  22690
5-9                  1686  10305
10-19                1228   8507
20-49                 926   7881
50-99                 263   3302
100-199               130   1649
200+                   11    391
```

[ ]:
```
             category        p_value     chi2_stat  \
0          teacher_id   2.464681e-67  78938.730161
1      teacher_prefix   3.197045e-18     88.186065
2  teacher_experience  1.470607e-151    721.663325

   project_is_approved_dependent_on_category  cramers_v      effect
0                                          1   0.850038      Strong
1                                          1   0.028411  Negligible
2                                          1   0.081276  Negligible
```

[ ]:
```python
teacher_exp_df = df[['teacher_number_of_previously_posted_projects',␣
 ↪'project_is_approved']]
teacher_exp_df['teacher_exp'] = np.
 ↪where(df['teacher_number_of_previously_posted_projects']==0, 'new',␣
 ↪'experienced')
teacher_exp_df.head()
```

[ ]:
```
   teacher_number_of_previously_posted_projects  project_is_approved  \
0                                            53                    1
1                                             4                    1
2                                            10                    1
3                                             2                    1
4                                             2                    1

   teacher_exp
0  experienced
1  experienced
2  experienced
3  experienced
4  experienced
```

[ ]:
```
ttest(df=teacher_exp_df,
      num_col='project_is_approved',
      cat_col='teacher_exp')
```

```
   teacher_exp  project_is_approved
0  experienced             0.858899
1          new             0.821350
```

[ ]:
```
      numerical_column categorical_column      means     t_stat       p_value  \
0  project_is_approved        teacher_exp  different  14.821018  1.366658e-49

  variances  levene_stat      levene_p  cohens_d effect
0   unequal    239.38154  6.122098e-54  0.104866   Weak
```

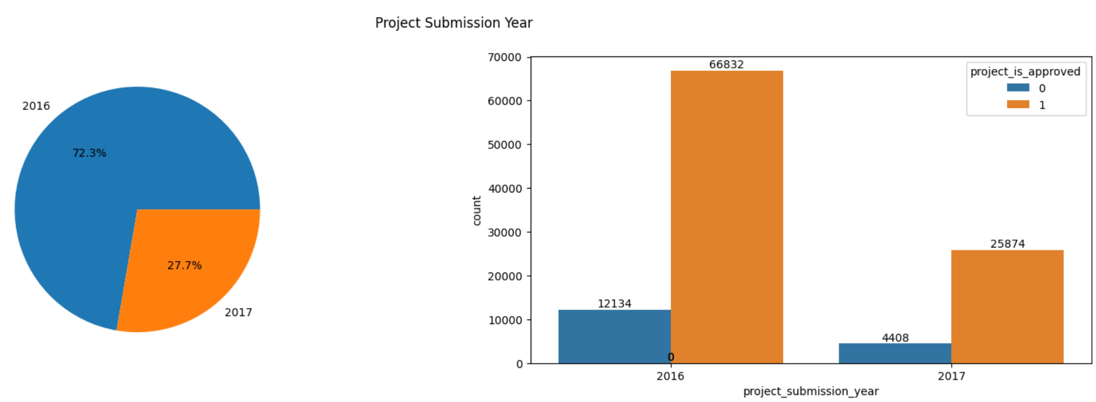
- **Significant Class Imbalance:** The dataset is heavily skewed, with **84.9%** of projects approved and only **15.1%** rejected. This means models must be carefully evaluated to avoid simply “guessing” approval for every entry.
- **Experience Correlation:** Approval rates increase linearly with the number of previously posted projects. Teachers with **0 projects** have an **82%** success rate, while veteran users with **200+ projects** reach a **97%** success rate.
- **Volume vs. Risk:** The vast majority of submissions come from new or relatively inexperienced teachers (0–4 projects). While they provide the most volume, they also represent the highest proportion of rejections.
- **Teacher Prefixes: “Mrs.”** and **“Ms.”** are the most active contributors by a wide margin. Teachers using the generic prefix **“Teacher”** show a slightly lower approval ratio compared to traditional titles.
- **Skewed Data Distribution:** The distribution of previous projects is highly “right-skewed,” with most teachers having under 10 projects and a few “power users” exceeding 400.
- **Data Preparation:** A **Log Transformation** effectively normalizes the “previous projects” feature, which is a necessary step for improving the performance of most machine learning algorithms.
- **Teacher identity is dominant:** `teacher_id` shows an extremely strong association with approval (Cramér’s V **0.85**) → approval is **highly teacher-dependent**.
- **Risk of leakage:** Using `teacher_id` directly in modeling will **inflate performance** and

hurt generalization.

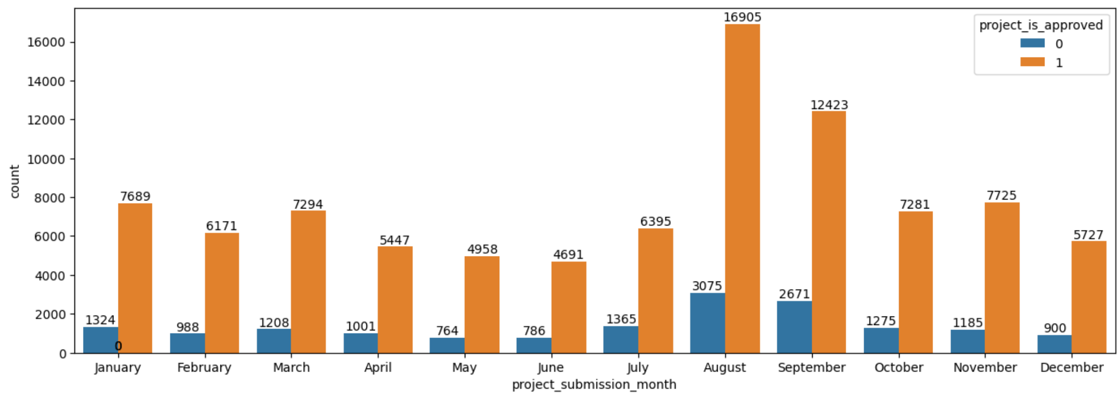
- **Teacher prefix is statistically significant but useless:** Very low effect size (V  **0.03**) → significance driven by large sample size, **no practical impact**.
- **Teacher experience (binned) is weak:** Despite tiny p-value, effect size is **negligible (V  0.08)** → experience alone barely shifts approval odds.
- **Experienced teachers mostly get approved:** Sample rows show approvals = 1 even at low experience counts → approval is common regardless of experience.
- **Mean difference exists but is small:** t-test shows significant difference in approvals by experience, but **Cohen's d  0.10 (weak)**.
- **Statistical vs practical gap:** Results highlight **statistical significance  business significance**.
- **Actionable takeaway:** Model should capture **teacher behavior history (aggregated features)**, not raw IDs or simple experience bins.

### 1.5.4 Project Submission time analysis

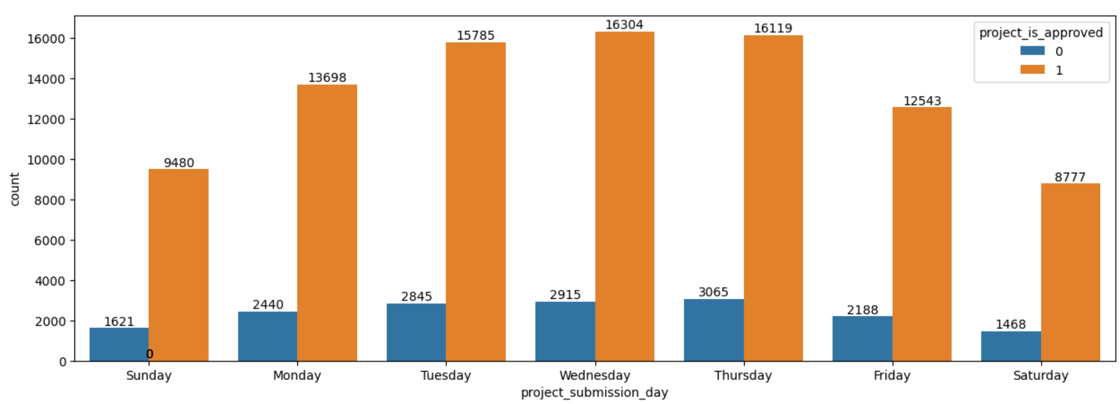
[ ]:
```
plt.figure(figsize=(20, 5))
plt.subplot(1, 2, 1)
plt.pie(df['project_submission_year'].value_counts(),
        labels=df['project_submission_year'].value_counts().index,
        autopct='%1.1f%%')

plt.subplot(1, 2, 2)
g = sns.countplot(data=df, x='project_submission_year',␣
 ↪hue='project_is_approved')
for p in g.patches:
    g.text(p.get_x() + p.get_width() / 2, p.get_height(), int(p.get_height()),␣
 ↪ha='center', va='bottom')

plt.suptitle("Project Submission Year")
plt.show()
```



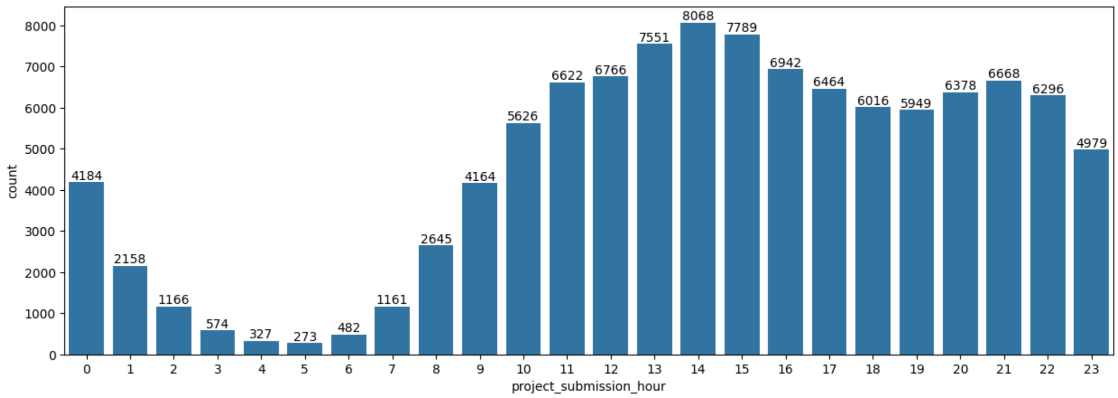
```
[ ]: months=['January', 'February', 'March', 'April', 'May', 'June', 'July',␣
      ↪'August', 'September', 'October', 'November', 'December']

     plt.figure(figsize=(15, 5))
     g = sns.countplot(data=df, x='project_submission_month',␣
      ↪hue='project_is_approved', order=months)
     for p in g.patches:
         g.text(p.get_x() + p.get_width() / 2, p.get_height(), int(p.get_height()),␣
      ↪ha='center', va='bottom')
     plt.show()
```



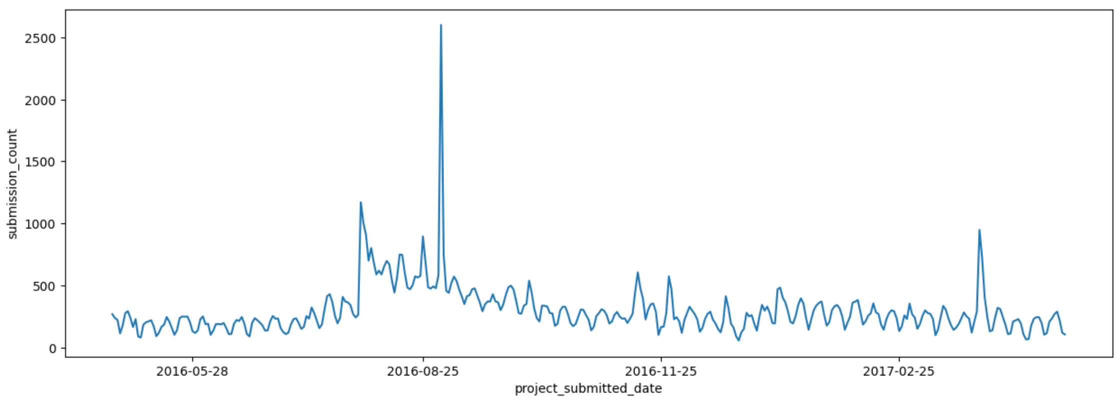

```
[ ]: days=['Sunday', 'Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday',␣
      ↪'Saturday']

     plt.figure(figsize=(15, 5))
     g = sns.countplot(data=df, x='project_submission_day',␣
      ↪hue='project_is_approved', order=days)
     for p in g.patches:
         g.text(p.get_x() + p.get_width() / 2, p.get_height(), int(p.get_height()),␣
      ↪ha='center', va='bottom')
     plt.show()
```



[ ]:
```
plt.figure(figsize=(15, 5))
g = sns.countplot(data=df, x='project_submission_hour')
for p in g.patches:
    g.text(p.get_x() + p.get_width() / 2, p.get_height(), int(p.get_height()),␣
 ↪ha='center', va='bottom')
plt.show()
```




[ ]:
```
import matplotlib.dates as mdates

submission_count_by_date = df.groupby('project_submitted_date').size().
 ↪reset_index(name='submission_count')

plt.figure(figsize=(15, 5))
sns.lineplot(data=submission_count_by_date, x='project_submitted_date',␣
 ↪y='submission_count')
plt.gca().xaxis.set_major_locator(mdates.MonthLocator(interval=3))
plt.show()
```



[ ]:
```
date_cols = ['project_submission_year', 'project_submission_month',␣
 ↪'project_submission_day', 'project_submission_hour']

chisquare_test(df, columns=date_cols, target_col='project_is_approved')
```

```
project_is_approved          0      1
project_submission_year
2016                     12134  66832
2017                      4408  25874

project_is_approved          0      1
project_submission_month
April                     1001   5447
August                    3075  16905
December                   900   5727
February                   988   6171
January                   1324   7689
July                      1365   6395
June                       786   4691
March                     1208   7294
May                        764   4958
November                  1185   7725
October                   1275   7281
September                 2671  12423

project_is_approved        0      1
project_submission_day
Friday                  2188  12543
Monday                  2440  13698
Saturday                1468   8777
Sunday                  1621   9480
Thursday                3065  16119
Tuesday                 2845  15785
Wednesday               2915  16304

project_is_approved        0     1
project_submission_hour
0                        713  3471
1                        378  1780
2                        181   985
3                        102   472
4                         56   271
5                         40   233
6                         81   401
7                        169   992
8                        385  2260
```

```
9                            582   3582
10                           844   4782
11                          1017   5605
12                          1014   5752
13                          1126   6425
14                          1216   6852
15                          1143   6646
16                          1058   5884
17                           972   5492
18                           845   5171
19                           896   5053
20                           925   5453
21                          1057   5611
22                           940   5356
23                           802   4177
```

[ ]:
```
                  category       p_value   chi2_stat  \
0   project_submission_year  8.619551e-04   11.102842
1  project_submission_month  8.830142e-34  185.154744
2    project_submission_day  3.526575e-03   19.408505
3   project_submission_hour  1.534661e-03   48.292661

   project_is_approved_dependent_on_category  cramers_v      effect
0                                          1   0.010081  Negligible
1                                          1   0.041168  Negligible
2                                          1   0.013329  Negligible
3                                          1   0.021025  Negligible
```

[ ]:
```python
chisquare_test(df, columns=date_cols, target_col='teacher_id', table=False)
```

[ ]:
```
                  category        p_value     chi2_stat  \
0   project_submission_year   2.174243e-19  7.561142e+04
1  project_submission_month  2.647994e-318  8.428464e+05
2    project_submission_day   9.346121e-53  4.473404e+05
3   project_submission_hour   7.774609e-11  1.671528e+06

   teacher_id_dependent_on_category  cramers_v  effect
0                                 1   0.831930  Strong
1                                 1   0.837474  Strong
2                                 1   0.826108  Strong
3                                 1   0.815617  Strong
```

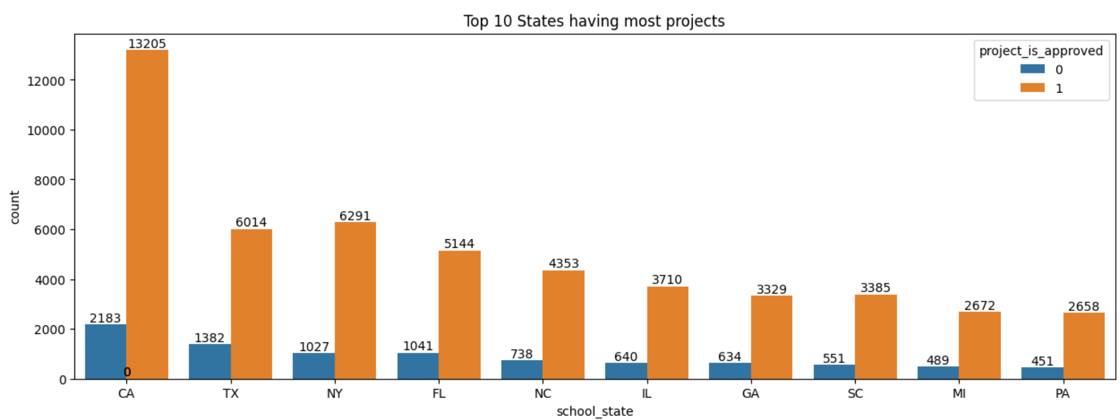
- **Massive Seasonal Surge:** Submissions and approvals peak dramatically in **August** (16,905 approved) due to the back-to-school season.
- **Weekly Rhythm:** Project activity is highest mid-week, peaking on **Wednesday** (16,304 approved) and **Thursday**, while dropping significantly on weekends.
- **Peak Submission Hour:** Teachers are most active during the day, with submissions peaking

at **2:00 PM (14:00)**.

- **Annual Data Split:** The dataset is predominantly composed of projects from **2016** (72.3%) compared to 2017 (27.7%).
- **Consistent Approval Ratio:** Despite large fluctuations in volume (daily spikes and seasonal peaks), the approval-to-rejection ratio remains relatively stable.
- **Time has negligible impact on approval:** Year, month, day, and hour are statistically significant but all have **near-zero effect sizes (Cramér's V $< 0.05$)** → timing does **not meaningfully influence approval**.
- **Seasonality  approval driver:** Even strong month-level significance does **not translate to practical approval differences**.
- **Teacher timing is highly structured:** Submission time is **strongly dependent on teacher_id** (Cramér's V  **0.82–0.84**) → teachers submit at **consistent personal times**.
- **Hidden confounding:** Apparent temporal patterns mostly reflect **teacher behavior**, not system preference.

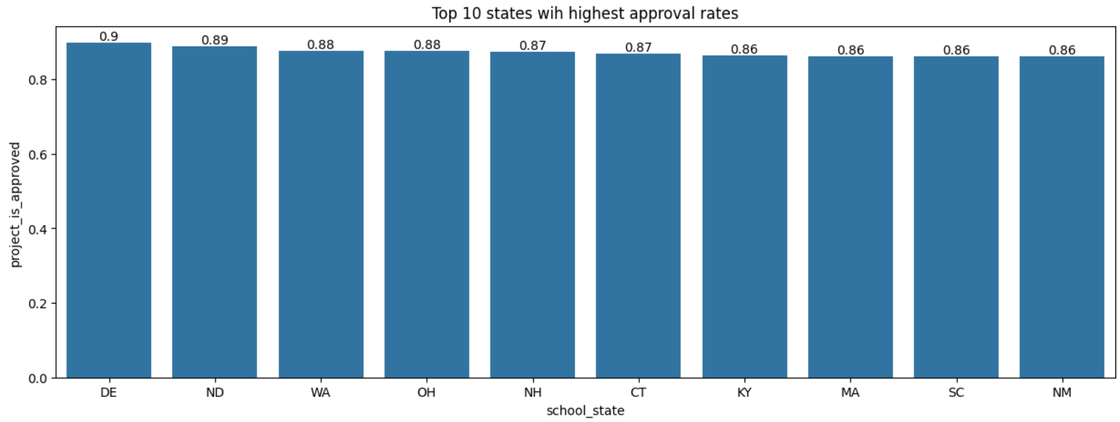
### 1.5.5 School State

[ ]:
```python
plt.figure(figsize=(15, 5))

top_10_states = df['school_state'].value_counts().head(10).index

g = sns.countplot(data=df[df['school_state'].isin(top_10_states)],
                  order=top_10_states,
                  x='school_state',
                  hue='project_is_approved')
for p in g.patches:
    g.text(p.get_x() + p.get_width() / 2, p.get_height(), int(p.get_height()),␣
 ↪ha='center', va='bottom')

plt.title("Top 10 States having most projects")
plt.show()
```



[ ]:
```python
# approval rate by state
state_approval_rate = df.groupby('school_state')['project_is_approved'].mean().
↪reset_index()

# visualize map of states with approval rate
import plotly.express as px


# Create the choropleth map
fig = px.choropleth(
    state_approval_rate,
    locations='school_state',
    locationmode='USA-states',
    color='project_is_approved',
    hover_name='school_state',
    color_continuous_scale='Viridis',
    scope='usa',
    title='Approval Rates by State'
)


# Update layout and display map
fig.update_layout(
    geo=dict(showframe=False, showcoastlines=True, projection_type='albers␣
↪usa'),
    margin=dict(l=10, r=10, t=50, b=10)
)

fig.show()
```

[ ]:
```python
# top 10 state with approval rate
state_approval_rate = state_approval_rate.sort_values(by='project_is_approved',␣
↪ascending=False)

plt.figure(figsize=(15, 5))
g = sns.barplot(data=state_approval_rate.head(10), x='school_state',␣
↪y='project_is_approved')
for p in g.patches:
    g.text(p.get_x() + p.get_width() /2, p.get_height(), round(p.get_height(),␣
↪2), ha='center', va='bottom')
plt.title('Top 10 states wih highest approval rates')
plt.show()
```




[ ]:
```
chisquare_test(df, columns='school_state', target_col='project_is_approved')
```

```
project_is_approved     0      1
school_state
AK                     55    290
AL                    256   1506
AR                    177    872
AZ                    347   1800
CA                   2183  13205
CO                    176    935
CT                    218   1445
DC                    102    414
DE                     35    308
FL                   1041   5144
GA                    634   3329
HI                     73    434
IA                     98    568
ID                    114    579
IL                    640   3710
IN                    406   2214
KS                    102    532
KY                    178   1126
LA                    404   1990
MA                    334   2055
MD                    244   1270
ME                     77    428
MI                    489   2672
MN                    172   1036
MO                    374   2202
MS                    205   1118
MT                     45    200
NC                    738   4353
```

```
ND                        16    127
NE                        49    260
NH                        44    304
NJ                       349   1888
NM                        78    479
NV                       200   1167
NY                      1027   6291
OH                       308   2159
OK                       376   1900
OR                       186   1056
PA                       451   2658
RI                        42    243
SC                       551   3385
SD                        48    252
TN                       253   1435
TX                      1382   6014
UT                       283   1448
VA                       306   1739
VT                        16     64
WA                       289   2045
WI                       282   1545
WV                        73    430
WY                        16     82
```

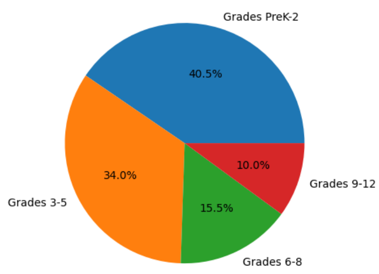
[ ]:
```
       category       p_value   chi2_stat  \
0  school_state  3.326378e-19  196.206742

   project_is_approved_dependent_on_category  cramers_v      effect
0                                          1   0.042379  Negligible
```

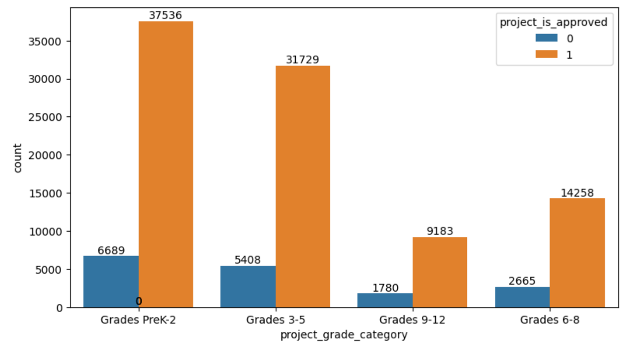
- **Highest Submission Volume: California (CA)** is the clear leader in total project volume, with **13,205** approved projects. Other high-volume states include Texas (TX), New York (NY), and Florida (FL).
- **Top Approval Rates:** While CA has the most projects, **Delaware (DE)** holds the highest approval rate at **0.9 (90%)**. North Dakota (ND) follows closely at **0.89**.
- **Statistical Impact:** The Chi-square test confirms that project approval is dependent on the school state. However, the **Cramer's V** value of **0.042** indicates that the actual strength of this association is **negligible**.

### 1.5.6 Grade

[ ]:
```
plt.figure(figsize=(20, 5))
plt.subplot(1, 2, 1)
plt.pie(df['project_grade_category'].value_counts(),
        labels=df['project_grade_category'].value_counts().index,
        autopct='%1.1f%%')
```

```
plt.subplot(1, 2, 2)
g = sns.countplot(data=df, x='project_grade_category',␣
↪hue='project_is_approved')
for p in g.patches:
    g.text(p.get_x() + p.get_width() / 2, p.get_height(), int(p.get_height()),␣
↪ha='center', va='bottom')
```




[ ]:
```
chisquare_test(df, columns='project_grade_category',␣
↪target_col='project_is_approved')
```

```
project_is_approved          0      1
project_grade_category
Grades 3-5                5408  31729
Grades 6-8                2665  14258
Grades 9-12               1780   9183
Grades PreK-2             6689  37536
```

[ ]:
```
                 category   p_value  chi2_stat  \
0  project_grade_category  0.000017  24.776179

   project_is_approved_dependent_on_category  cramers_v      effect
0                                          1   0.015059  Negligible
```

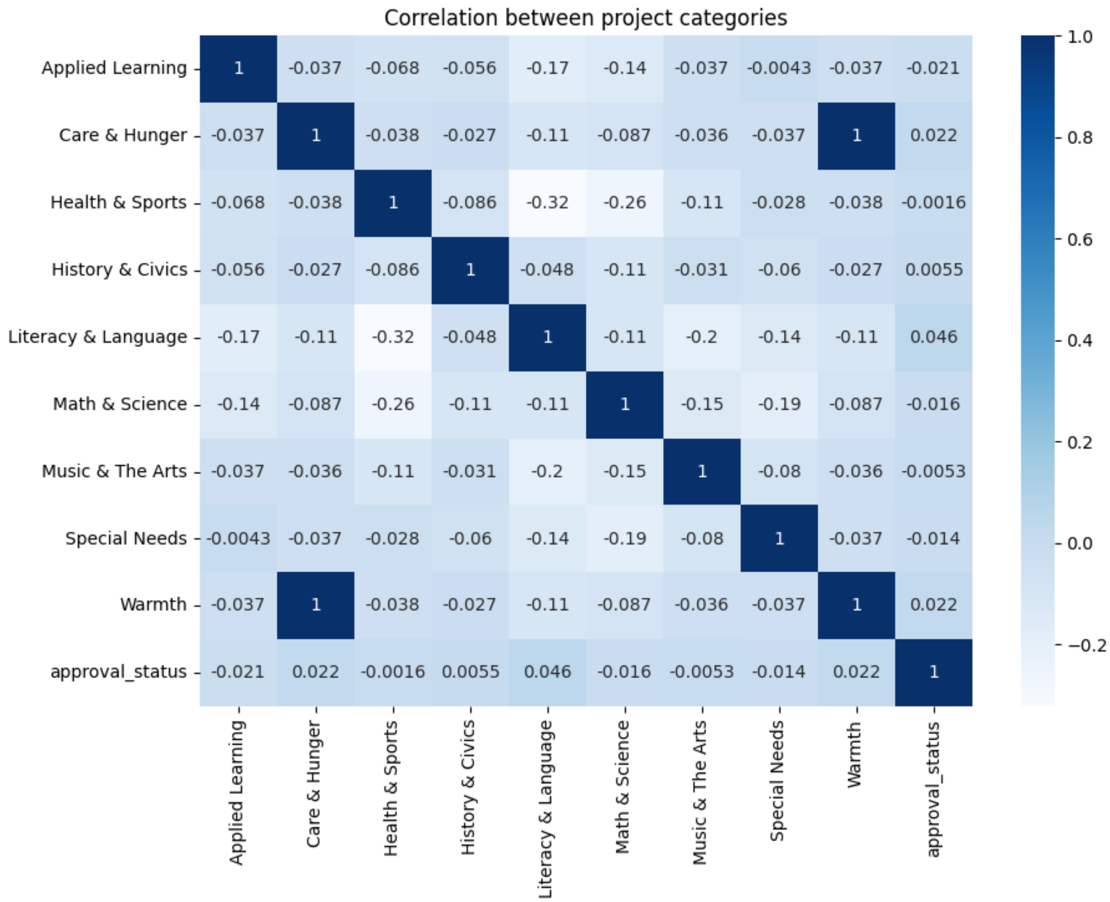
- **Dominant Groups: Grades PreK-2** is the largest category, accounting for **40.5%** of all projects. **Grades 3-5** follow closely with **34.0%**.
- **High School vs. Elementary:** High school projects (**Grades 9-12**) represent only **10.0%** of total submissions.
- **Approval Consistency:** Despite the large volume differences, the approval-to-rejection ratio remains relatively consistent across all grades. Statistical analysis shows that while approval is technically dependent on the grade category, the actual effect size is **negligible**.

### 1.5.7 Project Categories

[ ]:
```
proj_cat = df['project_subject_categories'].str.get_dummies(sep=', ')
proj_cat['approval_status'] = df['project_is_approved']
proj_cat.head()
```

[ ]:
```
   Applied Learning  Care & Hunger  Health & Sports  History & Civics  \
0                 0              0                0                 0
1                 0              0                0                 0
2                 0              0                0                 0
3                 1              0                0                 0
4                 0              0                0                 0

   Literacy & Language  Math & Science  Music & The Arts  Special Needs  \
0                    0               1                 0              0
1                    0               0                 0              1
2                    1               0                 0              0
3                    0               0                 0              0
4                    1               0                 0              0

   Warmth  approval_status
0       0                1
1       0                1
2       0                1
3       0                1
4       0                1
```

[ ]:
```
plt.figure(figsize=(10, 7))
sns.heatmap(proj_cat.corr(), cmap='Blues', annot=True)
plt.title('Correlation between project categories')
plt.show()
```



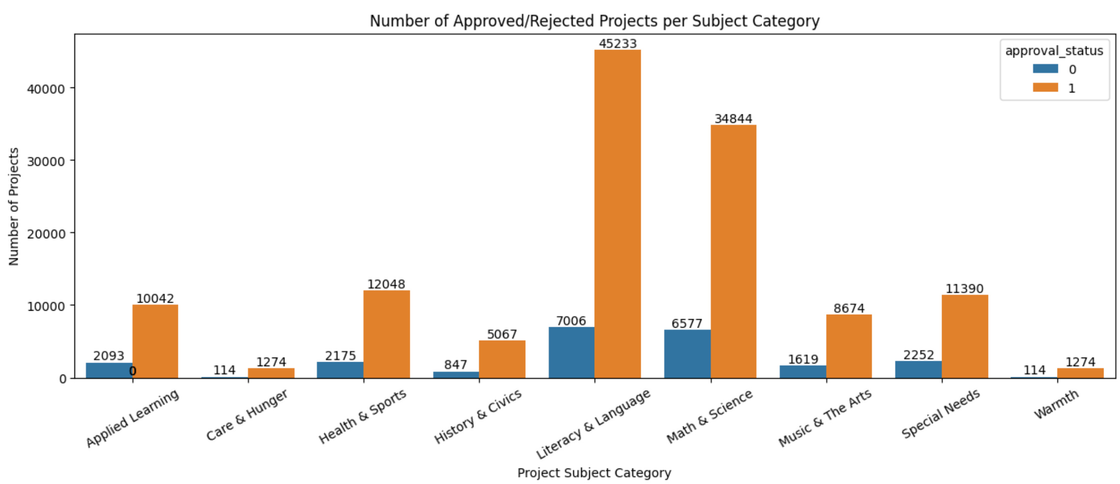

```
[ ]: cols = proj_cat.columns[:-1]
     proj_cat_df = proj_cat.groupby('approval_status')[cols].sum().reset_index()
     proj_cat_df
```

```
[ ]:    approval_status  Applied Learning  Care & Hunger  Health & Sports  \
     0                0              2093            114             2175
     1                1             10042           1274            12048

        History & Civics  Literacy & Language  Math & Science  Music & The Arts  \
     0               847                 7006            6577              1619
     1              5067                45233           34844              8674

        Special Needs  Warmth
     0           2252     114
     1          11390    1274
```

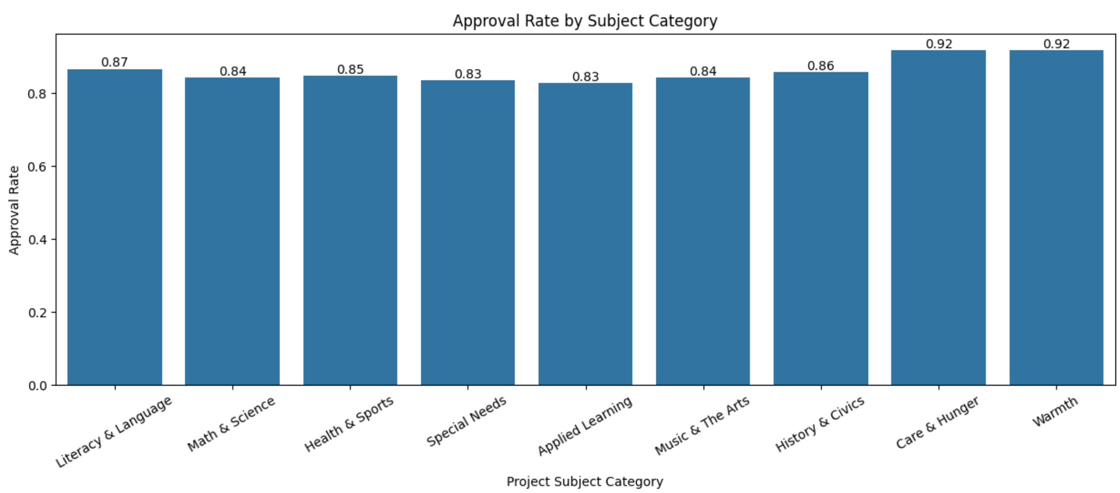
```
[ ]: proj_cat_df_reordered = proj_cat_df.T.sort_values(by=1, ascending=False).
      ↪head(10)
     proj_cat_df_reordered
```

```
[ ]:                         0      1
     Literacy & Language  7006  45233
     Math & Science       6577  34844
     Health & Sports      2175  12048
     Special Needs        2252  11390
     Applied Learning     2093  10042
     Music & The Arts     1619   8674
     History & Civics      847   5067
     Care & Hunger         114   1274
     Warmth                114   1274
     approval_status         0      1
```

```
[ ]: # Melt the DataFrame to long format for easier plotting with seaborn
     proj_cat_melted = proj_cat_df.melt(id_vars='approval_status',
                                        var_name='category',
                                        value_name='count')

     plt.figure(figsize=(15, 5))
     g = sns.barplot(data=proj_cat_melted, x='category', y='count',␣
      ↪hue='approval_status')
     for p in g.patches:
         g.text(p.get_x() + p.get_width() / 2, p.get_height(), int(p.get_height()),␣
      ↪ha='center', va='bottom')

     plt.xticks(rotation=30)
     plt.ylabel('Number of Projects')
     plt.xlabel('Project Subject Category')
     plt.title('Number of Approved/Rejected Projects per Subject Category')
     plt.show()
```

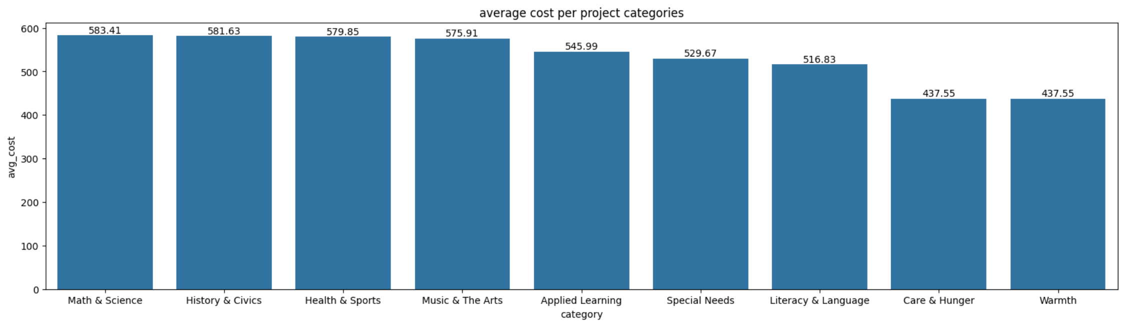


```
[ ]: # approval rate by project category
proj_cat_df_reordered['approval_rate'] = proj_cat_df_reordered[1] /
 ↪(proj_cat_df_reordered[0] + proj_cat_df_reordered[1])
proj_cat_df_reordered = proj_cat_df_reordered.iloc[:-1]
plt.figure(figsize=(15, 5))
g = sns.barplot(data=proj_cat_df_reordered.reset_index(), x='index',
 ↪y='approval_rate')
for p in g.patches:
    g.text(p.get_x() + p.get_width() / 2, p.get_height(), p.get_height().
 ↪round(2), ha='center', va='bottom')

plt.xticks(rotation=30)
plt.ylabel('Approval Rate')
plt.xlabel('Project Subject Category')
plt.title('Approval Rate by Subject Category')
plt.show()
```




```
[ ]: proj_cat['total_project_cost'] = df['total_resource_cost'].copy()

# average cost per category
cols = proj_cat.columns[:-2]

category = []
avg_cost = []
for col in cols:
  category.append(col)
  avg_cost.append(proj_cat[proj_cat[col] == 1]['total_project_cost'].mean())

proj_cat_cost_df = pd.DataFrame({'category': category, 'avg_cost': avg_cost})
proj_cat_cost_df = proj_cat_cost_df.sort_values(by='avg_cost', ascending=False)
```

```
# bar plot for average cost per category
plt.figure(figsize=(20, 5))
g = sns.barplot(data=proj_cat_cost_df, x='category', y='avg_cost')
for p in g.patches:
  g.text(p.get_x() + p.get_width() / 2, p.get_height(), round(p.get_height(),␣
↪2), ha='center', va='bottom')

plt.title('average cost per project categories')
plt.show()
```




[ ]:
```
cols = proj_cat.columns[:-2]
chisquare_test(proj_cat, cols, target_col='approval_status')
```

```
approval_status       0      1
Applied Learning
0                 14449  82664
1                  2093  10042

approval_status     0      1
Care & Hunger
0               16428  91432
1                 114   1274

approval_status     0      1
Health & Sports
0               14367  80658
1                2175  12048

approval_status       0      1
History & Civics
0                 15695  87639
1                   847   5067

approval_status          0      1
```

```
Literacy & Language
0                    9536  47473
1                    7006  45233

approval_status     0      1
Math & Science
0                9965  57862
1                6577  34844

approval_status       0      1
Music & The Arts
0                 14923  84032
1                  1619   8674

approval_status      0      1
Special Needs
0                14290  81316
1                 2252  11390

approval_status      0      1
Warmth
0                16428  91432
1                  114   1274
```

[ ]:

```
             category       p_value   chi2_stat  \
0    Applied Learning  7.338451e-12   46.934892
1       Care & Hunger  5.613579e-13   51.977656
2     Health & Sports  6.001931e-01    0.274705
3    History & Civics  7.350936e-02    3.202866
4  Literacy & Language  1.327954e-52  232.990496
5      Math & Science  1.158212e-07   28.089690
6    Music & The Arts  8.317837e-02    3.001677
7       Special Needs  2.077937e-06   22.521602
8              Warmth  5.613579e-13   51.977656

   approval_status_dependent_on_category  cramers_v      effect
0                                      1   0.020727  Negligible
1                                      1   0.021812  Negligible
2                                      0   0.001586  Negligible
3                                      0   0.005415  Negligible
4                                      1   0.046181  Negligible
5                                      1   0.016035  Negligible
6                                      0   0.005242  Negligible
7                                      1   0.014358  Negligible
8                                      1   0.021812  Negligible
```

- **Volume Leaders: Literacy & Language** is the most popular category by a massive margin, with 45,233 approved projects. **Math & Science** follows as the second most active category with 34,844 approvals.

- **Highest Approval Rates:** While high-volume categories have solid success rates, the niche categories **Care & Hunger** and **Warmth** boast the highest individual approval probability at **92%**.
- **Statistical Independence:** Although some categories show statistically significant dependencies (p-values $< 0.05$), the **Cramer's V** values for all categories are below 0.05, indicating the subject category has a **negligible effect** on the final approval status.
- **Most Expensive Categories: Math & Science** projects require the highest funding on average at **USD 583.41**, followed closely by History & Civics and Health & Sports.
- **Most Affordable Projects:** The categories with the highest approval rates (**Care & Hunger** and **Warmth**) are also the most affordable, with an identical average cost of **USD 437.55**.
- **Funding Strategy:** There appears to be an inverse relationship between project cost and approval rate; lower-cost essential categories (Warmth, Hunger) are approved more frequently than higher-cost technical ones (Math & Science).
- **Yearly Volume Shift: 2016** accounted for the vast majority of the dataset with **72.3%** of projects (66,832 approved) compared to only 27.7% in 2017.
- **Category Overlap:** The correlation heatmap reveals a perfect correlation (1.0) between **Care & Hunger** and **Warmth**, suggesting these categories are almost always selected together by teachers.
- **Literacy Correlation:** Literacy & Language shows a slight negative correlation with Math & Science (-0.11), suggesting teachers typically focus their funding requests on one of these core pillars rather than both simultaneously.

#### 1.5.8 Project Sub categories

[ ]:
```
proj_sub_cat = df['project_subject_subcategories'].str.get_dummies(sep=', ')
proj_sub_cat['approval_status'] = df['project_is_approved']
proj_sub_cat.head()
```

[ ]:
```
   Applied Sciences  Care & Hunger  Character Education  Civics & Government  \
0                 1              0                    0                    0
1                 0              0                    0                    0
2                 0              0                    0                    0
3                 0              0                    0                    0
4                 0              0                    0                    0

   College & Career Prep  Community Service  ESL  Early Development  \
0                      0                  0    0                  0
1                      0                  0    0                  0
2                      0                  0    0                  0
3                      0                  0    0                  1
4                      0                  0    0                  0

   Economics  Environmental Science  …  Nutrition Education  Other  \
0          0                      0  …                    0      0
```

```
1          0                      0  ...                    0       0
2          0                      0  ...                    0       0
3          0                      0  ...                    0       0
4          0                      0  ...                    0       0

   Parent Involvement  Performing Arts  Social Sciences  Special Needs  \
0                   0                0                0              0
1                   0                0                0              1
2                   0                0                0              0
3                   0                0                0              0
4                   0                0                0              0

   Team Sports  Visual Arts  Warmth  approval_status
0            0            0       0                1
1            0            0       0                1
2            0            0       0                1
3            0            0       0                1
4            0            0       0                1

[5 rows x 31 columns]
```

[ ]:
```
proj_sub_cat.corr()['approval_status'].sort_values(ascending=False)
```

[ ]:
```
approval_status           1.000000
Literacy                  0.045600
Care & Hunger             0.021926
Warmth                    0.021926
Music                     0.015914
Literature & Writing      0.014365
Health & Wellness         0.012673
Social Sciences           0.005387
Performing Arts           0.005372
History & Geography       0.003825
ESL                       0.001986
Parent Involvement        0.001793
Civics & Government      -0.000177
Financial Literacy       -0.000708
Economics                -0.001169
Gym & Fitness            -0.002087
Mathematics              -0.002578
Extracurricular          -0.004272
College & Career Prep    -0.005421
Other                    -0.009433
Foreign Languages        -0.010011
Nutrition Education      -0.011266
Health & Life Science    -0.012270
Community Service        -0.012575
```

```
Early Development        -0.012919
Special Needs            -0.014397
Character Education      -0.016375
Environmental Science    -0.017896
Visual Arts              -0.018697
Applied Sciences         -0.019774
Team Sports              -0.022781
Name: approval_status, dtype: float64
```

[ ]:
```
cols = proj_sub_cat.columns[:-1]
proj_sub_cat_df = proj_sub_cat.groupby('approval_status')[cols].sum()
proj_sub_cat_df
```

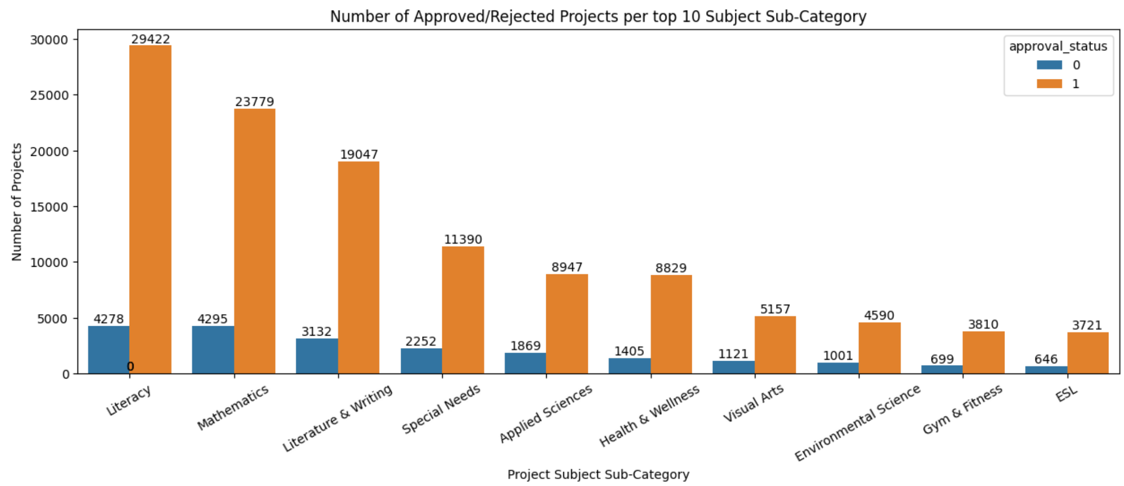
[ ]:
```
                 Applied Sciences  Care & Hunger  Character Education  \
approval_status
0                            1869            114                  400
1                            8947           1274                 1665

                 Civics & Government  College & Career Prep  \
approval_status
0                                124                    421
1                                691                   2147

                 Community Service   ESL  Early Development  Economics  \
approval_status
0                               98   646                742         43
1                              343  3721               3512        226

                 Environmental Science  …  Music  Nutrition Education  \
approval_status                         …
0                                 1001  …    372                  254
1                                 4590  …   2773                 1101

                 Other  Parent Involvement  Performing Arts  Social Sciences  \
approval_status
0                  413                  97              269              263
1                 1959                 580             1692             1657

                 Special Needs  Team Sports  Visual Arts  Warmth
approval_status
0                         2252          457         1121     114
1                        11390         1735         5157    1274

[2 rows x 30 columns]
```

[ ]:
```
proj_sub_cat_df_t10 = proj_sub_cat_df.T.sort_values(by=1, ascending=False).
 ↪head(10)
```

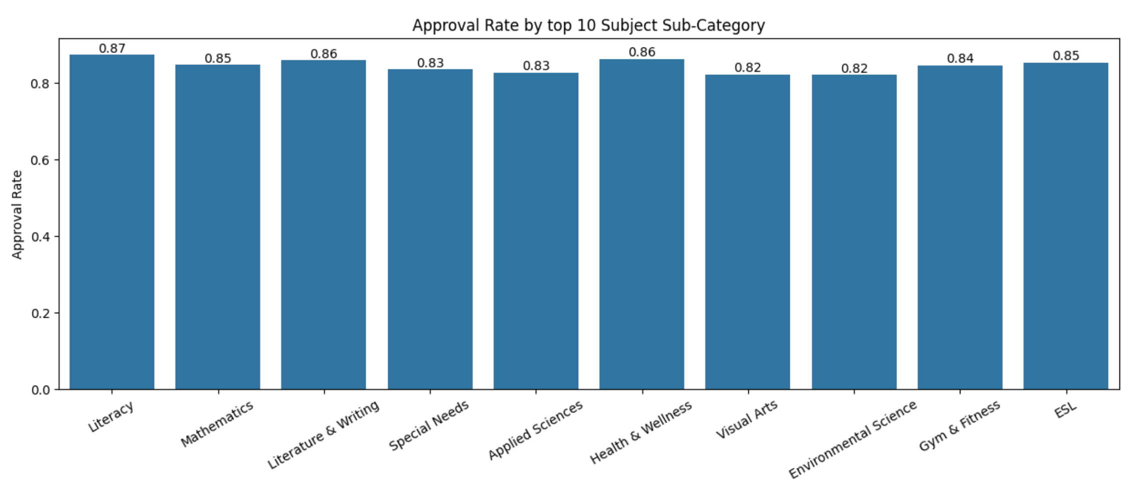
```
proj_sub_cat_df_t10
```

```
[ ]: approval_status           0      1
     Literacy               4278  29422
     Mathematics            4295  23779
     Literature & Writing   3132  19047
     Special Needs          2252  11390
     Applied Sciences       1869   8947
     Health & Wellness      1405   8829
     Visual Arts            1121   5157
     Environmental Science  1001   4590
     Gym & Fitness           699   3810
     ESL                     646   3721
```

```
[ ]: # Melt the DataFrame to long format for easier plotting
proj_sub_cat_melted = proj_sub_cat_df_t10.reset_index().melt(
    id_vars='index',
    value_vars=[0, 1],
    var_name='approval_status',
    value_name='count'
)

proj_sub_cat_melted = proj_sub_cat_melted.rename(columns={'index': 'category'})

plt.figure(figsize=(15, 5))
g = sns.barplot(data=proj_sub_cat_melted, x='category', y='count',␣
 ↪hue='approval_status')
for p in g.patches:
    g.text(p.get_x() + p.get_width() / 2, p.get_height(), int(p.get_height()),␣
 ↪ha='center', va='bottom')

plt.xticks(rotation=30)
plt.ylabel('Number of Projects')
plt.xlabel('Project Subject Sub-Category')
plt.title('Number of Approved/Rejected Projects per top 10 Subject␣
 ↪Sub-Category')
plt.show()
```

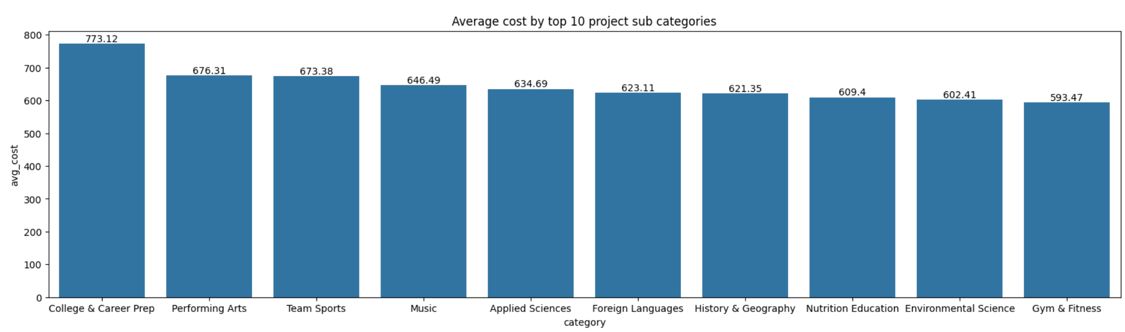



```
[ ]: # approval rate by project sub-category
proj_sub_cat_df_t10['approval_rate'] = proj_sub_cat_df_t10[1] /␣
 ↪(proj_sub_cat_df_t10[0] + proj_sub_cat_df_t10[1])

plt.figure(figsize=(15, 5))
g = sns.barplot(data=proj_sub_cat_df_t10.reset_index(), x='index',␣
 ↪y='approval_rate')
for p in g.patches:
    g.text(p.get_x() + p.get_width() / 2, p.get_height(), p.get_height().
 ↪round(2), ha='center', va='bottom')

plt.xticks(rotation=30)
plt.ylabel('Approval Rate')
plt.xlabel('Project Subject Sub-Category')
plt.title('Approval Rate by top 10 Subject Sub-Category')
plt.show()
```



[ ]:

```
proj_sub_cat['total_project_cost'] = df['total_resource_cost'].copy()

# average cost per category
cols = proj_sub_cat.columns[:-2]

category = []
avg_cost = []
for col in cols:
  category.append(col)
  avg_cost.append(proj_sub_cat[proj_sub_cat[col] == 1]['total_project_cost'].
↪mean())

proj_sub_cat_cost_df = pd.DataFrame({'category': category, 'avg_cost':␣
↪avg_cost})
proj_sub_cat_cost_df = proj_sub_cat_cost_df.sort_values(by='avg_cost',␣
↪ascending=False)

# bar plot for top 10 sub categories average cost
plt.figure(figsize=(20, 5))
g = sns.barplot(data=proj_sub_cat_cost_df.head(10), x='category', y='avg_cost')
for p in g.patches:
  g.text(p.get_x() + p.get_width() / 2, p.get_height(), round(p.get_height(),␣
↪2), ha='center', va='bottom')

plt.title('Average cost by top 10 project sub categories')
plt.show()
```




[ ]:

```
cols = proj_sub_cat.columns[:-2]
chisquare_test(proj_sub_cat, cols,target_col='approval_status')
```

```
approval_status       0      1
Applied Sciences
0                 14673  83759
```

```
1                  1869   8947

approval_status      0      1
Care & Hunger
0               16428  91432
1                 114   1274

approval_status          0      1
Character Education
0                   16142  91041
1                     400   1665

approval_status          0      1
Civics & Government
0                   16418  92015
1                     124    691

approval_status            0      1
College & Career Prep
0                     16121  90559
1                       421   2147

approval_status        0      1
Community Service
0                 16444  92363
1                    98    343

approval_status      0      1
ESL
0               15896  88985
1                 646   3721

approval_status        0      1
Early Development
0                 15800  89194
1                   742   3512

approval_status      0      1
Economics
0               16499  92480
1                  43    226

approval_status            0      1
Environmental Science
0                     15541  88116
1                      1001   4590

approval_status      0      1
```

```
Extracurricular
0                16405  92033
1                  137    673

approval_status         0      1
Financial Literacy
0                   16454  92226
1                      88    480

approval_status        0      1
Foreign Languages
0                  16372  91986
1                    170    720

approval_status      0      1
Gym & Fitness
0                15843  88896
1                  699   3810

approval_status            0      1
Health & Life Science
0                      15808  89205
1                        734   3501

approval_status        0      1
Health & Wellness
0                  15137  83877
1                   1405   8829

approval_status          0      1
History & Geography
0                    16087  89990
1                      455   2716

approval_status      0      1
Literacy
0                12264  63284
1                 4278  29422

approval_status           0      1
Literature & Writing
0                     13410  73659
1                      3132  19047

approval_status      0      1
Mathematics
0                12247  68927
1                 4295  23779
```

```
approval_status      0      1
Music
0                16170  89933
1                  372   2773

approval_status          0      1
Nutrition Education
0                    16288  91605
1                      254   1101

approval_status      0      1
Other
0                16129  90747
1                  413   1959

approval_status         0      1
Parent Involvement
0                   16445  92126
1                      97    580

approval_status      0      1
Performing Arts
0                16273  91014
1                  269   1692

approval_status      0      1
Social Sciences
0                16279  91049
1                  263   1657

approval_status      0      1
Special Needs
0                14290  81316
1                 2252  11390

approval_status      0      1
Team Sports
0                16085  90971
1                  457   1735

approval_status      0      1
Visual Arts
0                15421  87549
1                 1121   5157

approval_status      0      1
Warmth
```

|   |   |   |
|---|---|---|
| 0 | 16428 | 91432 |
| 1 | 114 | 1274 |

[ ]:

|    | category | p_value | chi2_stat |
|---|---|---|---|
| 0 | Applied Sciences | 6.953451e-11 | 42.532021 |
| 1 | Care & Hunger | 5.613579e-13 | 51.977656 |
| 2 | Character Education | 7.394062e-08 | 28.958631 |
| 3 | Civics & Government | 9.925513e-01 | 0.000087 |
| 4 | College & Career Prep | 7.775746e-02 | 3.111162 |
| 5 | Community Service | 4.314627e-05 | 16.727706 |
| 6 | ESL | 5.254350e-01 | 0.403212 |
| 7 | Early Development | 2.152919e-05 | 18.048998 |
| 8 | Economics | 7.632314e-01 | 0.090746 |
| 9 | Environmental Science | 3.727935e-09 | 34.760859 |
| 10 | Extracurricular | 1.729182e-01 | 1.857460 |
| 11 | Financial Literacy | 8.607071e-01 | 0.030791 |
| 12 | Foreign Languages | 1.106907e-03 | 10.639615 |
| 13 | Gym & Fitness | 5.036589e-01 | 0.447218 |
| 14 | Health & Life Science | 5.494239e-05 | 16.269460 |
| 15 | Health & Wellness | 2.990913e-05 | 17.423588 |
| 16 | History & Geography | 2.153571e-01 | 1.535043 |
| 17 | Literacy | 2.844888e-51 | 226.887874 |
| 18 | Literature & Writing | 2.163762e-06 | 22.443859 |
| 19 | Mathematics | 3.994754e-01 | 0.709905 |
| 20 | Music | 1.651274e-07 | 27.403555 |
| 21 | Nutrition Education | 2.280519e-04 | 13.584573 |
| 22 | Other | 2.008237e-03 | 9.541992 |
| 23 | Parent Involvement | 5.900515e-01 | 0.290264 |
| 24 | Performing Arts | 8.121649e-02 | 3.040388 |
| 25 | Social Sciences | 8.037983e-02 | 3.057205 |
| 26 | Special Needs | 2.077937e-06 | 22.521602 |
| 27 | Team Sports | 6.396528e-14 | 56.245463 |
| 28 | Visual Arts | 7.190239e-10 | 37.968329 |
| 29 | Warmth | 5.613579e-13 | 51.977656 |

\

|    | approval_status_dependent_on_category | cramers_v | effect |
|---|---|---|---|
| 0 | 1 | 0.019731 | Negligible |
| 1 | 1 | 0.021812 | Negligible |
| 2 | 1 | 0.016281 | Negligible |
| 3 | 0 | 0.000028 | Negligible |
| 4 | 0 | 0.005336 | Negligible |
| 5 | 1 | 0.012374 | Negligible |
| 6 | 0 | 0.001921 | Negligible |
| 7 | 1 | 0.012853 | Negligible |
| 8 | 0 | 0.000911 | Negligible |
| 9 | 1 | 0.017838 | Negligible |

```
10                                                   0   0.004123  Negligible
11                                                   0   0.000531  Negligible
12                                                   1   0.009869  Negligible
13                                                   0   0.002023  Negligible
14                                                   1   0.012203  Negligible
15                                                   1   0.012629  Negligible
16                                                   0   0.003748  Negligible
17                                                   1   0.045572  Negligible
18                                                   1   0.014333  Negligible
19                                                   0   0.002549  Negligible
20                                                   1   0.015838  Negligible
21                                                   1   0.011151  Negligible
22                                                   1   0.009346  Negligible
23                                                   0   0.001630  Negligible
24                                                   0   0.005275  Negligible
25                                                   0   0.005290  Negligible
26                                                   1   0.014358  Negligible
27                                                   1   0.022690  Negligible
28                                                   1   0.018642  Negligible
29                                                   1   0.021812  Negligible
```

- **Sub-Category Popularity: Literacy** is the most frequent sub-category with 29,422 approved projects, followed by **Mathematics** with 23,779.
- **High Success Rates:** While smaller in volume, the sub-categories **Care & Hunger** and **Warmth** maintain the highest individual approval rates at **92%**.
- **Financial Variations: College & Career Prep** is the most expensive sub-category on average at **USD 773.12**, whereas **Gym & Fitness** is among the most affordable at **USD 593.47**.
- **Approval Correlation:** The **Literacy** sub-category shows the strongest positive correlation with project approval (0.0456), whereas **Team Sports** has the strongest negative correlation (-0.0227).
- **Statistical Impact:** Chi-square tests for various sub-categories (e.g., Applied Sciences, Literacy, Special Needs) show p-values below 0.05, confirming a statistical dependency on approval status.

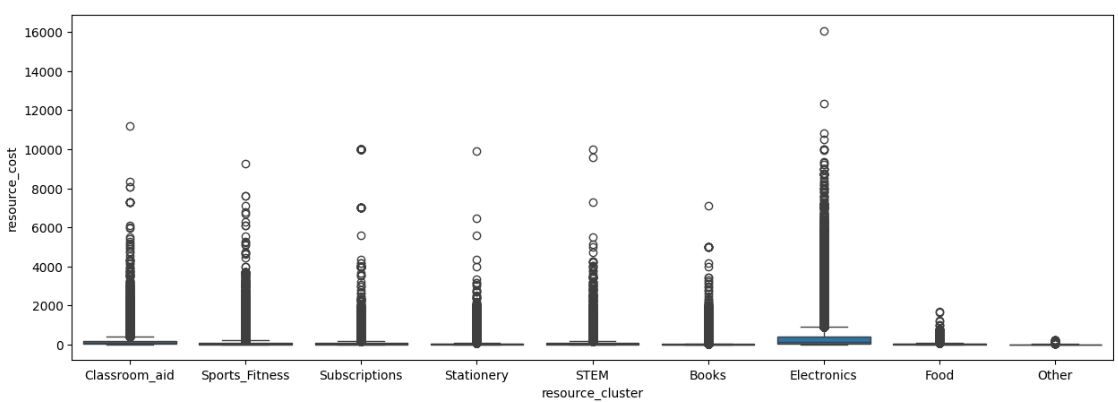
### 1.5.9 Resource cluster analysis

[ ]:
```
resources.head()
```

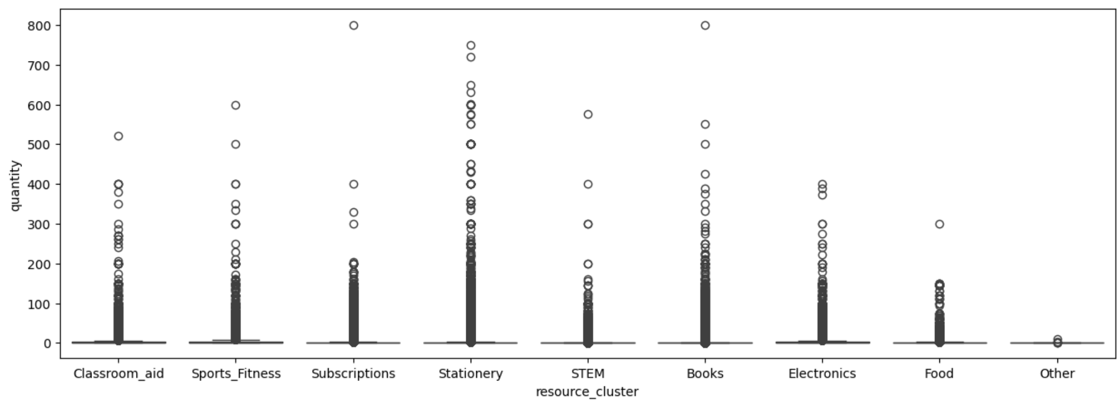
[ ]:
```
        id                                         description  quantity  \
0  p233245  LC652 - Lakeshore Double-Space Mobile Drying Rack         1
1  p069063        Bouncy Bands for Desks (Blue support pipes)         3
2  p069063  Cory Stories: A Kid's Book About Living With Adhd         1
3  p069063  Dixon Ticonderoga Wood-Cased #2 HB Pencils, Bo…         2
4  p069063  EDUCATIONAL INSIGHTS FLUORESCENT LIGHT FILTERS…         3

   unit_price  resource_cost  \
```

```
0       149.00         149.00
1        14.95          44.85
2         8.45           8.45
3        13.59          27.18
4        24.95          74.85

                                 cleaned_description  kmeans_label  \
0        lc lakeshore doublespace mobile drying rack             7
1              bouncy bands desks blue support pipes            19
2                  cory stories kids book living adhd             3
3  dixon ticonderoga woodcased hb pencils box yellow             9
4  educational insights fluorescent light filters…             23

  resource_cluster
0    Classroom_aid
1   Sports_Fitness
2    Subscriptions
3       Stationery
4    Classroom_aid
```

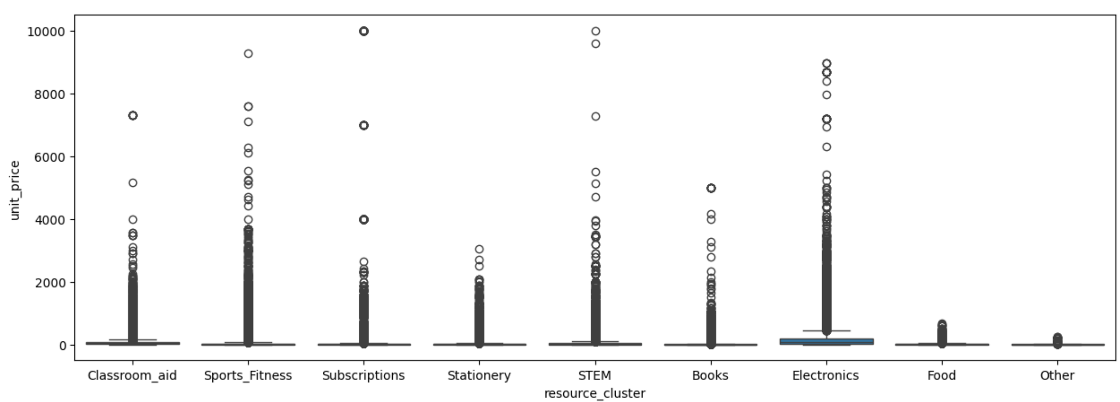
[ ]:
```
plt.figure(figsize=(15, 5))
sns.boxplot(data=resources, x='resource_cluster', y='resource_cost')
plt.show()
```




[ ]:
```
plt.figure(figsize=(15, 5))
sns.boxplot(data=resources, x='resource_cluster', y='quantity')
plt.show()
```



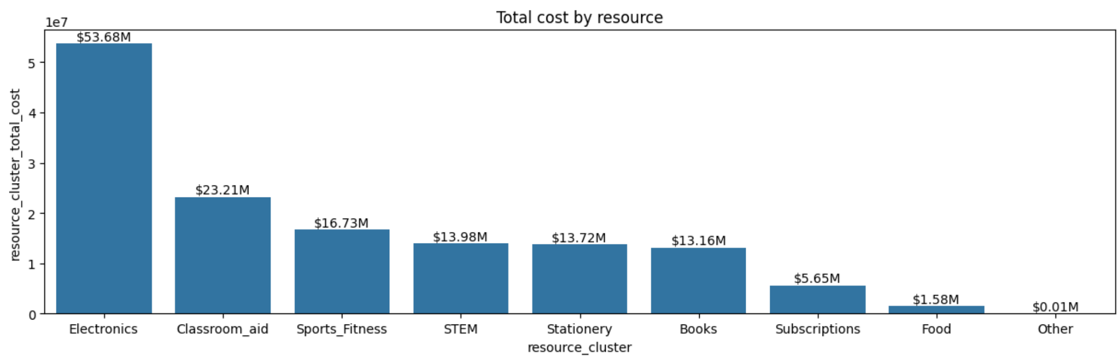

[ ]:
```python
plt.figure(figsize=(15, 5))
sns.boxplot(data=resources, x='resource_cluster', y='unit_price')
plt.show()
```



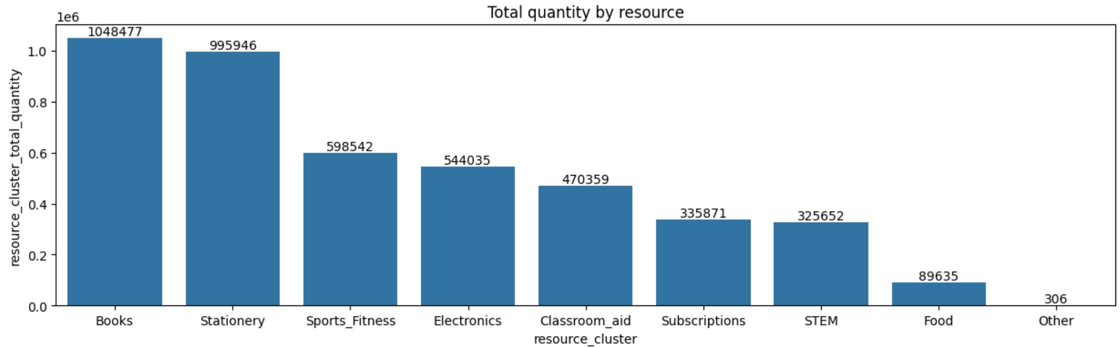

[ ]:
```python
resource_cluster_agg = (
    resources
    .groupby("resource_cluster", as_index=False)
    .agg(
        resource_cluster_count=("id", "count"),
        resource_cluster_total_cost=("resource_cost", "sum"),
        resource_cluster_total_quantity=("quantity", "sum"),
        resource_cluster_avg_item_cost=("unit_price", "mean")
    )
)

resource_cluster_agg
```

```
[ ]:  resource_cluster  resource_cluster_count  resource_cluster_total_cost  \
0              Books                  460650                  13156695.66
1      Classroom_aid                  159980                  23212632.07
2        Electronics                  168492                  53681494.14
3               Food                   42427                   1584217.19
4              Other                     292                      8848.25
5               STEM                  179386                  13984525.08
6     Sports_Fitness                  167179                  16728305.27
7         Stationery                  301893                  13724726.46
8      Subscriptions                   60973                   5650436.60

   resource_cluster_total_quantity  resource_cluster_avg_item_cost
0                          1048477                       17.832088
1                           470359                       78.566230
2                           544035                      157.867566
3                            89635                       20.905777
4                              306                       29.685890
5                           325652                       55.967668
6                           598542                       46.633779
7                           995946                       25.921302
8                           335871                       58.409194
```

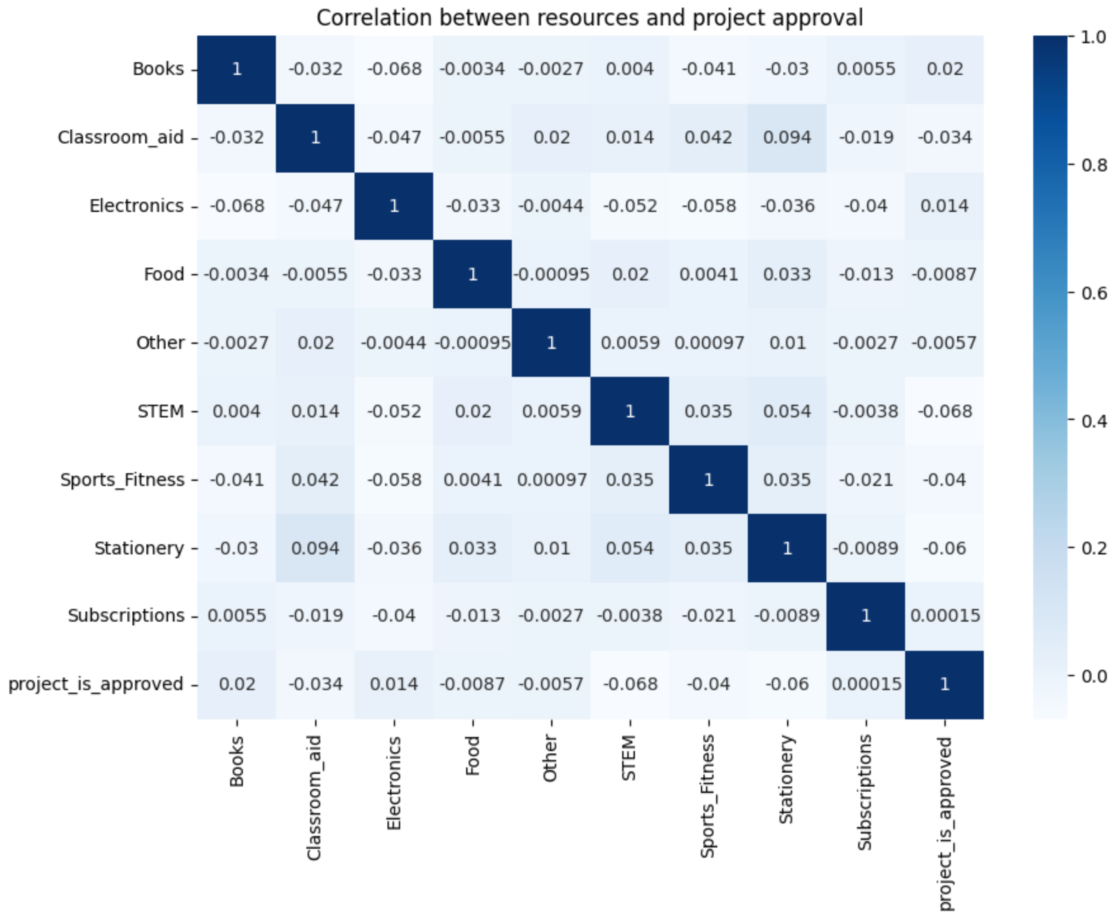
```
[ ]: plt.figure(figsize=(15, 4))
order = resource_cluster_agg.sort_values(by='resource_cluster_total_cost',␣
 ↪ascending=False)['resource_cluster']
g = sns.barplot(data=resource_cluster_agg, x="resource_cluster",␣
 ↪y="resource_cluster_total_cost", order=order)
for p in g.patches:
    g.text(p.get_x() + p.get_width() / 2, p.get_height(), '$'+ str((p.
 ↪get_height()/1000000).round(2)) + 'M', ha='center', va='bottom')
plt.title('Total cost by resource')
plt.show()
```



[ ]:
```python
plt.figure(figsize=(15, 4))
order = resource_cluster_agg.sort_values(by='resource_cluster_total_quantity',␣
↪ascending=False)['resource_cluster']
g = sns.barplot(data=resource_cluster_agg, x="resource_cluster",␣
↪y="resource_cluster_total_quantity", order=order)
for p in g.patches:
    g.text(p.get_x() + p.get_width() / 2, p.get_height(), int(p.get_height()),␣
↪ha='center', va='bottom')
plt.title('Total quantity by resource')
plt.show()
```




[ ]:
```python
resource_cols = resource_cluster_agg.resource_cluster.unique()
resource_approval_df = df[resource_cols.tolist() + ['project_is_approved']]
resource_corr = resource_approval_df.corr()

plt.figure(figsize=(10, 7))
sns.heatmap(resource_corr, cmap='Blues', annot=True)
plt.title('Correlation between resources and project approval')
plt.show()
```

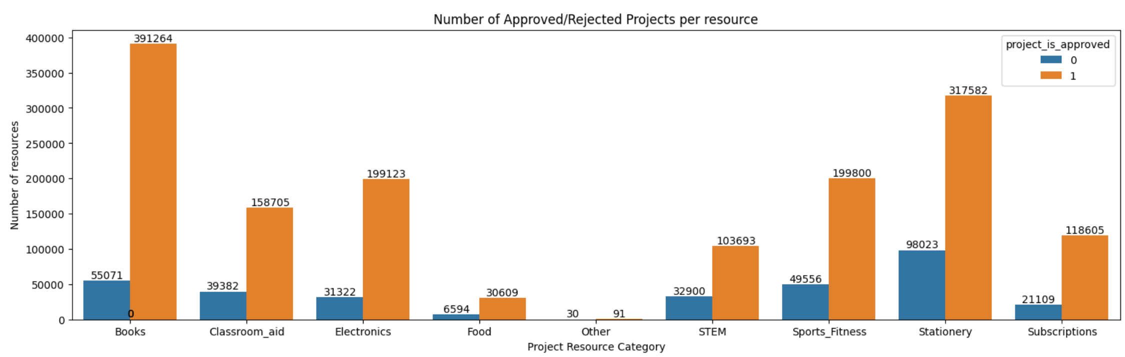



```
[ ]: resources_approval_group = resource_approval_df.
      ↪groupby('project_is_approved')[resource_cols].sum().reset_index()
     resources_approval_group
```

```
[ ]:    project_is_approved    Books  Classroom_aid  Electronics   Food  Other  \
     0                    0    55071          39382        31322   6594     30
     1                    1   391264         158705       199123  30609     91

          STEM  Sports_Fitness  Stationery  Subscriptions
     0   32900           49556       98023          21109
     1  103693          199800      317582         118605
```

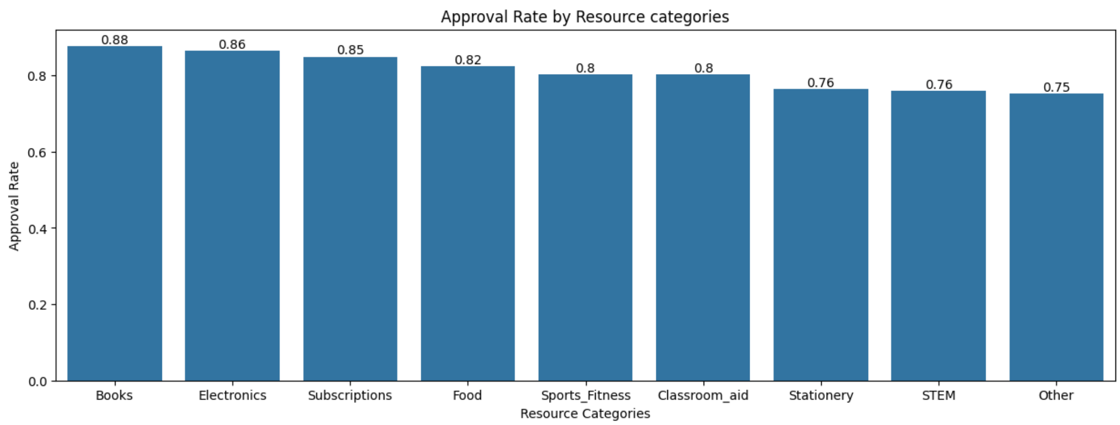
```
[ ]: # Melt the DataFrame to long format for easier plotting with seaborn
     resources_approval_group_melted = resources_approval_group.
      ↪melt(id_vars='project_is_approved',
                                         var_name='category',
                                         value_name='count')
```

```
plt.figure(figsize=(18, 5))
g = sns.barplot(data=resources_approval_group_melted, x='category', y='count',␣
 ↪hue='project_is_approved')
for p in g.patches:
    g.text(p.get_x() + p.get_width() / 2, p.get_height(), int(p.get_height()),␣
 ↪ha='center', va='bottom')

plt.ylabel('Number of resources')
plt.xlabel('Project Resource Category')
plt.title('Number of Approved/Rejected Projects per resource')
plt.show()
```




[ ]:
```
# Calculate approval rate by resource category
resources_approval_rate_df = pd.DataFrame(columns=['category', 'approval_rate'])
resource_cols = resources_approval_group.columns[1:] # Exclude␣
 ↪'project_is_approved'
for col in resource_cols:
    approved_count = resources_approval_group.
 ↪loc[resources_approval_group['project_is_approved'] == 1, col].iloc[0]
    rejected_count = resources_approval_group.
 ↪loc[resources_approval_group['project_is_approved'] == 0, col].iloc[0]
    total_count = approved_count + rejected_count
    approval_rate = approved_count / total_count if total_count > 0 else 0
    resources_approval_rate_df = pd.concat([resources_approval_rate_df, pd.
 ↪DataFrame([{'category': col, 'approval_rate': approval_rate}])],␣
 ↪ignore_index=True)

# Sort by approval rate for better visualization
resources_approval_rate_df = resources_approval_rate_df.
 ↪sort_values(by='approval_rate', ascending=False)

plt.figure(figsize=(15, 5))
g = sns.barplot(data=resources_approval_rate_df, x='category',␣
 ↪y='approval_rate')
```

```python
for p in g.patches:
    g.text(p.get_x() + p.get_width() / 2, p.get_height(), round(p.get_height(),
 ↪2), ha='center', va='bottom')

plt.ylabel('Approval Rate')
plt.xlabel('Resource Categories')
plt.title('Approval Rate by Resource categories')
plt.show()
```




[ ]:
```python
chisquare_test(df, resource_cols, target_col='project_is_approved', table=False)
```

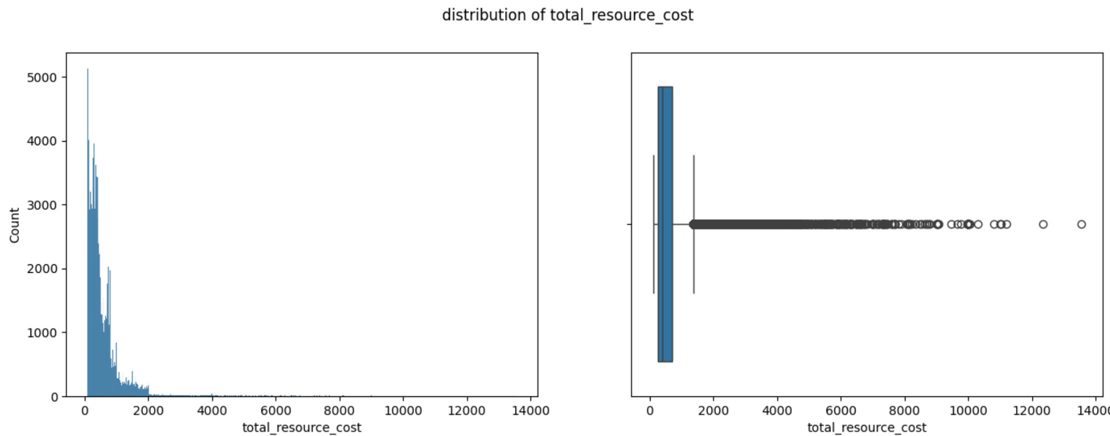
[ ]:

```
         category        p_value    chi2_stat  \
0           Books  1.113420e-100  1022.987188
1   Classroom_aid   1.310543e-88   781.464640
2     Electronics   2.757234e-06   180.423779
3            Food   5.748872e-34   344.988884
4           Other   1.800564e-02    15.306006
5            STEM   0.000000e+00  2244.268739
6  Sports_Fitness  4.436943e-232  1505.558048
7      Stationery   0.000000e+00  2913.940752
8   Subscriptions  2.076546e-184  1271.029807

   project_is_approved_dependent_on_category  cramers_v      effect
0                                          1   0.096767  Negligible
1                                          1   0.084576  Negligible
2                                          1   0.040639  Negligible
3                                          1   0.056195  Negligible
4                                          1   0.011837  Negligible
5                                          1   0.143328        Weak
6                                          1   0.117393        Weak
7                                          1   0.163318        Weak
8                                          1   0.107863        Weak
```

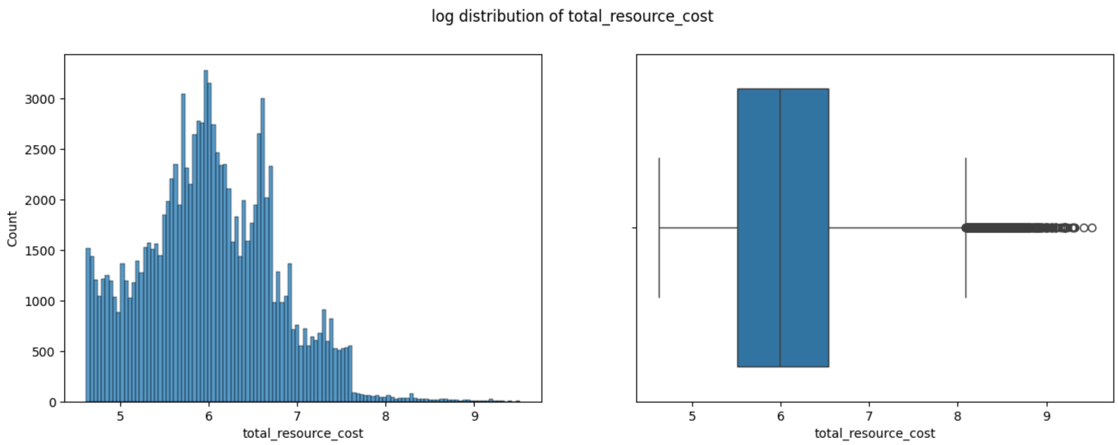
- **Total Resource Quantity: Books** represent the highest individual resource volume on the platform with **1,048,477** units requested, followed closely by **Stationery** at **995,946**.
- **Total Cost Leader:** Despite having a lower total quantity than books, **Electronics** accounts for the highest total expenditure at **USD 53.68M**, which is more than double the cost of the next category, Classroom Aid (USD 23.21M).
- **Approval Rate Trends:** Projects requesting **Books** have the highest approval probability at **88%**, whereas technical or high-cost categories like **STEM (76%)** and **Stationery (76%)** show lower approval rates.
- **Unit Price Variation: Electronics** has the highest average cost per item at **USD 157.87**, while **Books** are among the most affordable at **USD 17.83** per unit.
- **Approval Counts by Resource:** In terms of raw numbers, **Books** lead with **391,264** approved resources, while **Stationery** follows with **317,582** approved items.

### 1.5.10 Project Cost and resources quantity analysis

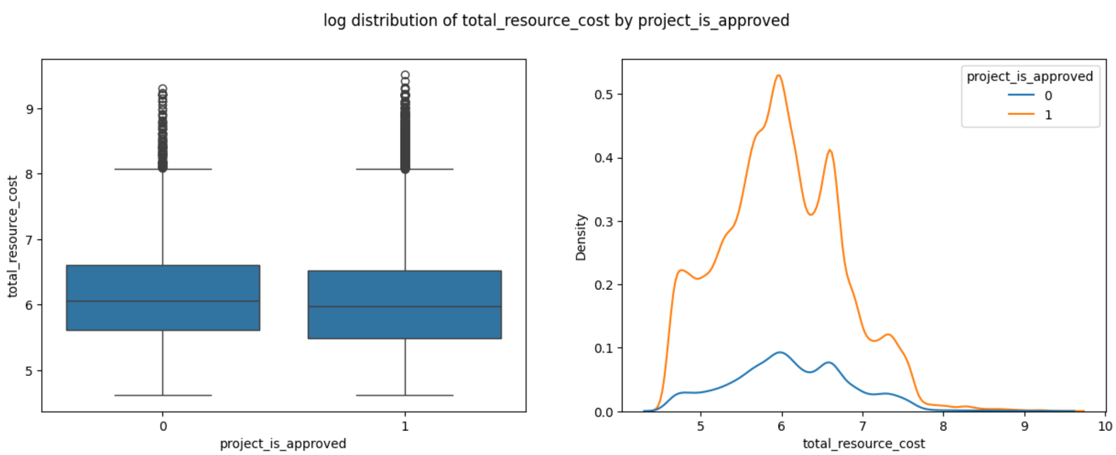
[ ]:
```
fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(15, 5))
sns.histplot(data=df, x='total_resource_cost', ax=ax[0])
sns.boxplot(data=df, x='total_resource_cost', ax=ax[1])
plt.suptitle('distribution of total_resource_cost')
plt.show()
```




[ ]:
```
log_cost_df = pd.DataFrame({
    'total_resource_cost': np.log1p(df['total_resource_cost']),
    'project_is_approved': df['project_is_approved'].astype('category')
})

fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(15, 5))
sns.histplot(data=log_cost_df, x='total_resource_cost', ax=ax[0])
sns.boxplot(data=log_cost_df, x='total_resource_cost', ax=ax[1])
plt.suptitle('log distribution of total_resource_cost')
plt.show()
```




```
[ ]: fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(15, 5))
     sns.boxplot(data=log_cost_df, y='total_resource_cost', x='project_is_approved',␣
      ↪ax=ax[0])
     sns.kdeplot(data=log_cost_df, x='total_resource_cost',␣
      ↪hue='project_is_approved', ax=ax[1])
     plt.suptitle('log distribution of total_resource_cost by project_is_approved')
     plt.show()
```



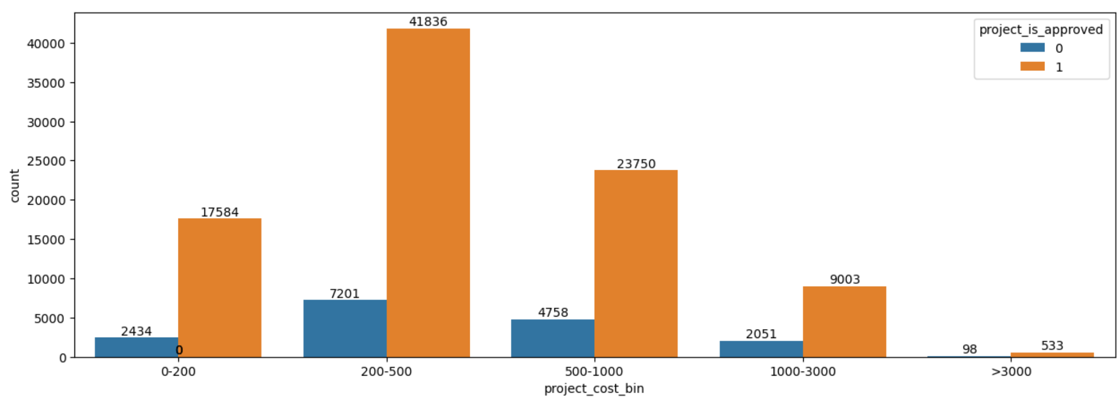

```
[ ]: ttest(df=log_cost_df,
           num_col='total_resource_cost',
           cat_col='project_is_approved')
```

```
  project_is_approved  total_resource_cost
0                   0             6.101457
1                   1             5.996815
```

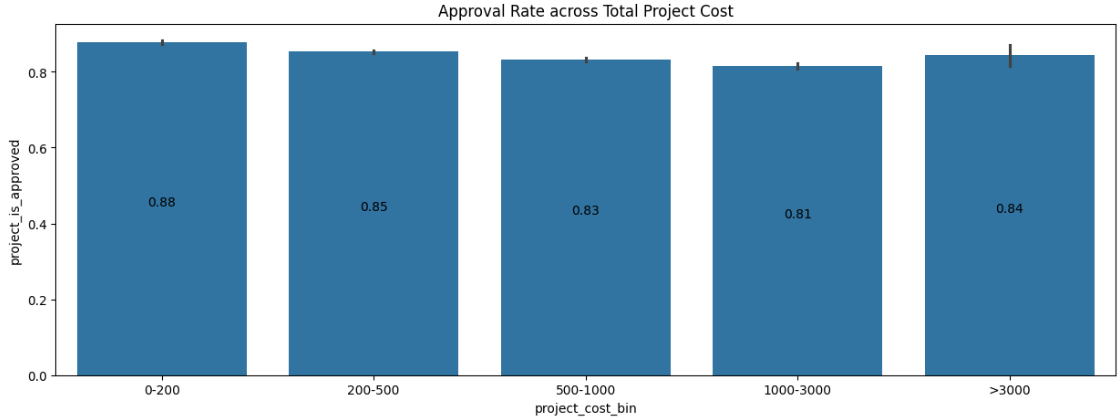
```
[ ]:        numerical_column   categorical_column      means     t_stat  \
     0  total_resource_cost  project_is_approved  different -16.840935

            p_value variances  levene_stat  levene_p  cohens_d effect
     0  1.471482e-63     equal     0.042971   0.83578 -0.142143   Weak
```

```
[ ]: bins = [0, 200, 500, 1000, 3000, df['total_resource_cost'].max()]
     labels = ['0-200', '200-500', '500-1000', '1000-3000', '>3000']

     df['project_cost_bin'] = pd.cut(df['total_resource_cost'], bins=bins,␣
      ↪labels=labels, include_lowest=True)
```

```
[ ]: plt.figure(figsize=(15, 5))
     g = sns.countplot(data=df, x='project_cost_bin', hue='project_is_approved')
     for p in g.patches:
         g.text(p.get_x() + p.get_width() / 2, p.get_height(), int(p.get_height()),␣
      ↪ha='center', va='bottom')
     plt.show()
```

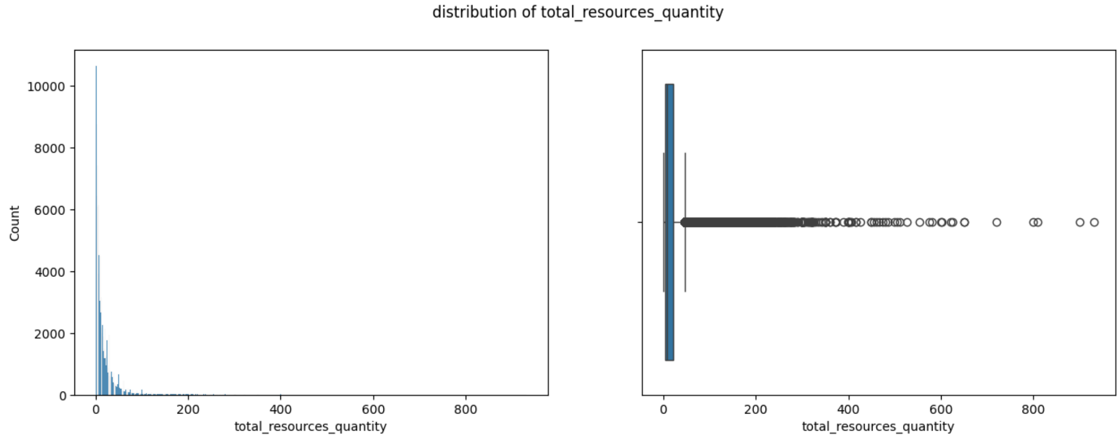



```
[ ]: # approval rate across project cost
     plt.figure(figsize=(15, 5))
     g = sns.barplot(data=df, x='project_cost_bin', y='project_is_approved')
     for p in g.patches:
         g.text(p.get_x() + p.get_width() / 2, p.get_height()/2, round(p.
      ↪get_height(), 2), ha='center', va='bottom')
     plt.title('Approval Rate across Total Project Cost')
     plt.show()
```



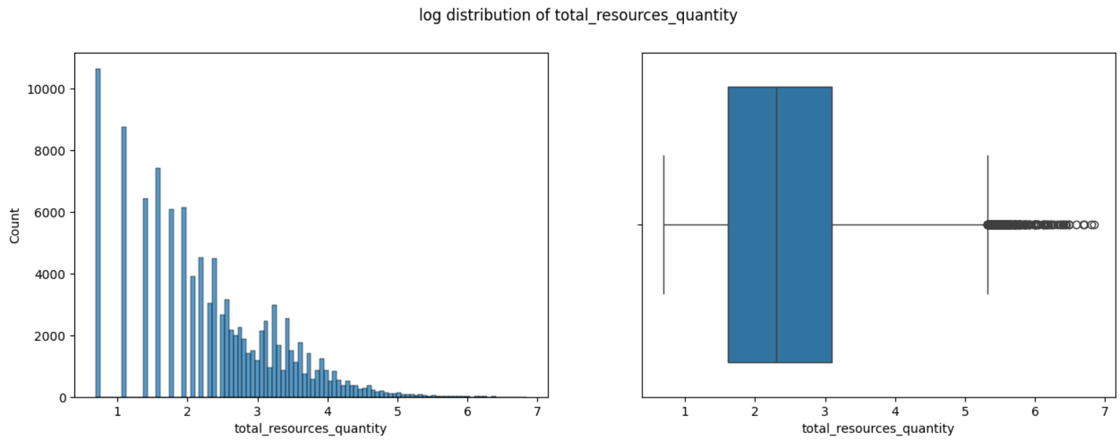

```
[ ]: df['total_resources_quantity'] = df['Electronics'] + df['Classroom_aid'] +␣
     ↪df['Sports_Fitness'] + df['STEM'] + df['Stationery'] + df['Books'] +␣
     ↪df['Subscriptions'] + df['Food'] + df['Other']
```

```
[ ]: fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(15, 5))
     sns.histplot(data=df, x='total_resources_quantity', ax=ax[0])
     sns.boxplot(data=df, x='total_resources_quantity', ax=ax[1])
     plt.suptitle('distribution of total_resources_quantity')
     plt.show()
```

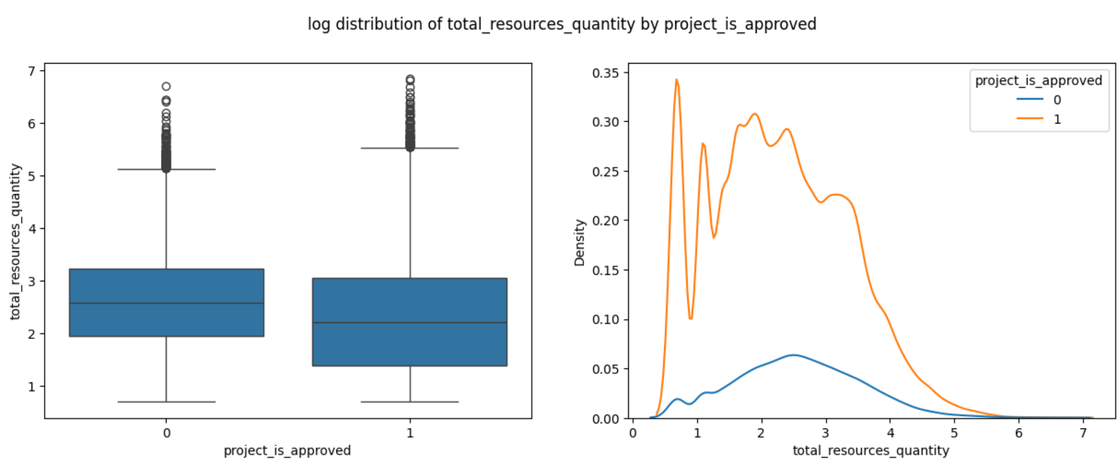



```
[ ]: log_cost_df = pd.DataFrame({
         'total_resources_quantity': np.log1p(df['total_resources_quantity']),
         'project_is_approved': df['project_is_approved'].astype('category')
     })

     fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(15, 5))
     sns.histplot(data=log_cost_df, x='total_resources_quantity', ax=ax[0])
```

```
sns.boxplot(data=log_cost_df, x='total_resources_quantity', ax=ax[1])
plt.suptitle('log distribution of total_resources_quantity')
plt.show()
```




```
[ ]: fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(15, 5))
sns.boxplot(data=log_cost_df, y='total_resources_quantity',␣
  ↪x='project_is_approved', ax=ax[0])
sns.kdeplot(data=log_cost_df, x='total_resources_quantity',␣
  ↪hue='project_is_approved', ax=ax[1])
plt.suptitle('log distribution of total_resources_quantity by␣
  ↪project_is_approved')
plt.show()
```




```
[ ]: ttest(df=log_cost_df,
       num_col='total_resources_quantity',
```

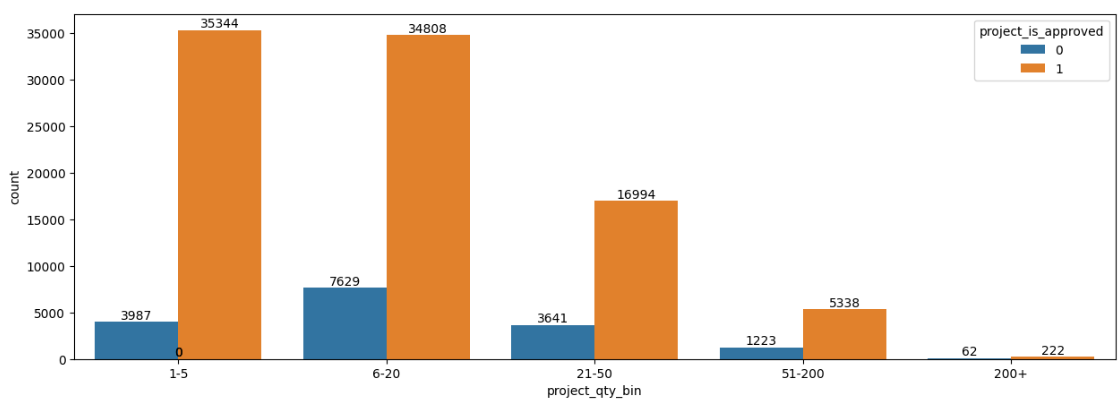
```
    cat_col='project_is_approved')
```

```
  project_is_approved  total_resources_quantity
0                    0                  2.567892
1                    1                  2.280299
```

[ ]:
```
           numerical_column   categorical_column      means     t_stat  \
0  total_resources_quantity  project_is_approved  different -35.024797

         p_value variances  levene_stat      levene_p  cohens_d effect
0  3.719125e-262   unequal   312.814542  6.664843e-70 -0.279686   Weak
```

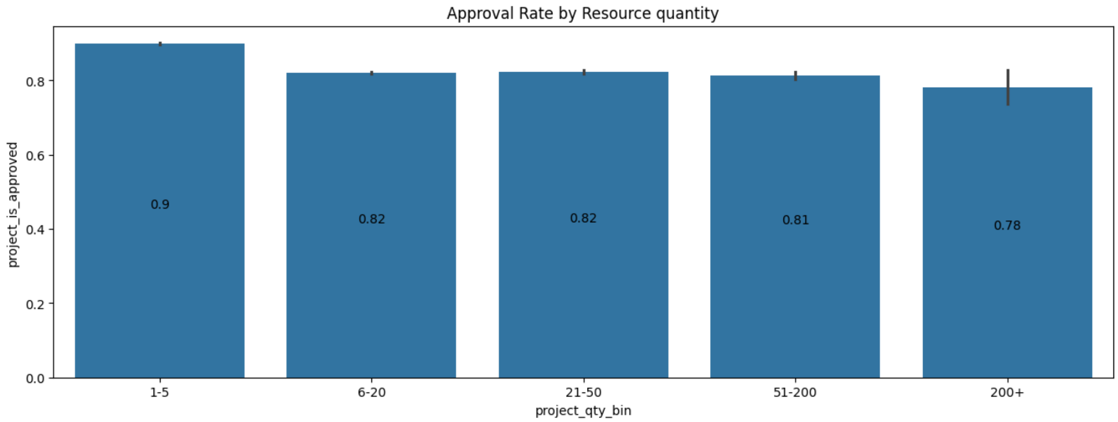
[ ]:
```
df['project_qty_bin'] = pd.cut(
    df['total_resources_quantity'],
    bins=[0,5,20,50,200, df['total_resources_quantity'].max()],
    labels=['1-5', '6-20', '21-50', '51-200', '200+'],
    include_lowest=True
)
```

[ ]:
```
plt.figure(figsize=(15, 5))
g = sns.countplot(data=df, x='project_qty_bin', hue='project_is_approved')
for p in g.patches:
    g.text(p.get_x() + p.get_width() / 2, p.get_height(), int(p.get_height()),␣
 ↪ha='center', va='bottom')
plt.show()
```

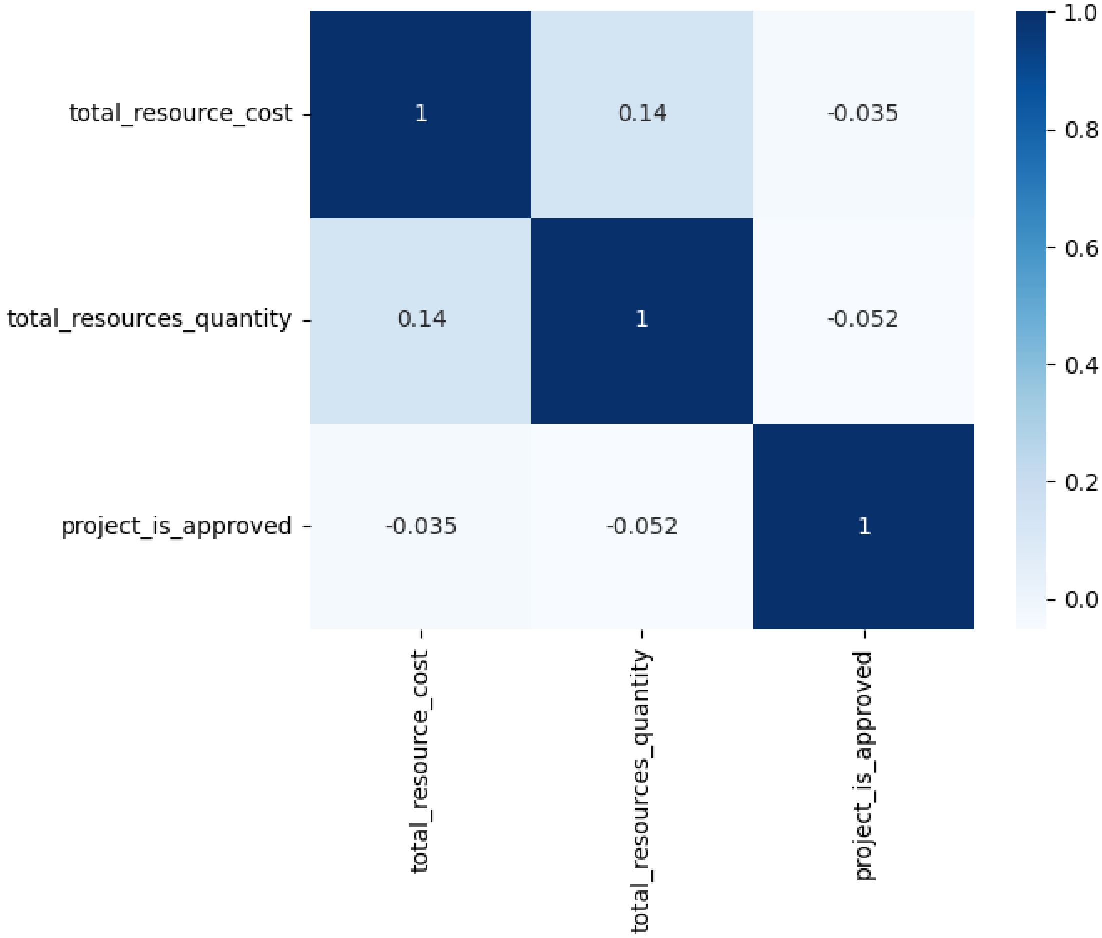



[ ]:
```
# approval rate by Resource quantity
plt.figure(figsize=(15, 5))
g = sns.barplot(data=df, x='project_qty_bin', y='project_is_approved')
for p in g.patches:
    g.text(p.get_x() + p.get_width() / 2, p.get_height()/2, round(p.
 ↪get_height(), 2), ha='center', va='bottom')
plt.title('Approval Rate by Resource quantity')
```

```
plt.show()
```




[ ]:
```
cost_cols=['total_resource_cost', 'total_resources_quantity',␣
↪'project_is_approved']

sns.heatmap(df[cost_cols].corr(), cmap='Blues', annot=True)
plt.show()
```




[ ]:
```
pearson_corr(df, col1='total_resource_cost', col2='project_is_approved')
```

[ ]:
```
               column1              column2  correlation       p_value  \
0  total_resource_cost  project_is_approved    -0.035026  5.183613e-31

  relation      effect
0  Related  Negligible
```

[ ]:
```
pearson_corr(df, col1='total_resources_quantity', col2='project_is_approved')
```

[ ]:
```
                    column1              column2  correlation       p_value  \
0  total_resources_quantity  project_is_approved    -0.052024  2.361665e-66

  relation      effect
0  Related  Negligible
```

- **Cost Distribution:** The distribution of `total_resource_cost` is heavily right-skewed with a significant number of high-cost outliers reaching up to **USD 14,000**.

- **Log Normalization:** Applying a log transformation to `total_resource_cost` reveals a multi-modal distribution, which helps stabilize the variance for predictive modeling.
- **Resource Correlation:** There is a weak positive correlation between **Books** and project approval (0.02), while **STEM (-0.068)** and **Stationery (-0.06)** show the strongest negative correlations with approval status.
- **Price Outliers:** Boxplots for `resource_cost` and `unit_price` highlight extreme outliers in the **Electronics** and **Sports/Fitness** clusters, with some individual units priced near **USD 10,000**.
- **Cost vs. Approval Success:** Projects with lower total resource costs have higher approval rates, with the **0–200 bin** leading at **88%** approval.
- **Approval Rate across Quantity:** Resource quantity shows a similar inverse trend, where smaller requests of **1–5 items** have the highest approval probability at **90%**.
- **Statistical Significance:** T-tests confirm that both total cost and quantity are significantly different between approved and rejected projects.
- **Effect Size:** Despite being statistically significant, both features show a **Weak** Cohen's d effect size (Cost: -0.14, Quantity: -0.28), indicating they are not the sole primary drivers of approval.
- **Correlation Metrics:** There is a **Negligible** negative correlation between approval and both cost (-0.035) and quantity (-0.052), suggesting that while lower values are better, the relationship is non-linear.
- **Data Skewness:** Both features are heavily right-skewed, requiring **log transformations** to normalize the distributions for effective machine learning modeling.
- **Cost Outliers:** The distribution of total resource cost includes extreme outliers reaching nearly **USD 14,000**, though the majority of projects fall below USD 2,000.
- **Quantity Outliers:** Similarly, while most projects request few items, some extreme cases request over **800 units**, which typically correlates with lower approval rates.

#### 1.5.11 project_title analysis

[ ]:
```
project_title_df = project_title_df.merge(df[['id', 'project_is_approved']],␣
↪on='id', how='left')
project_title_df.head(2)
```

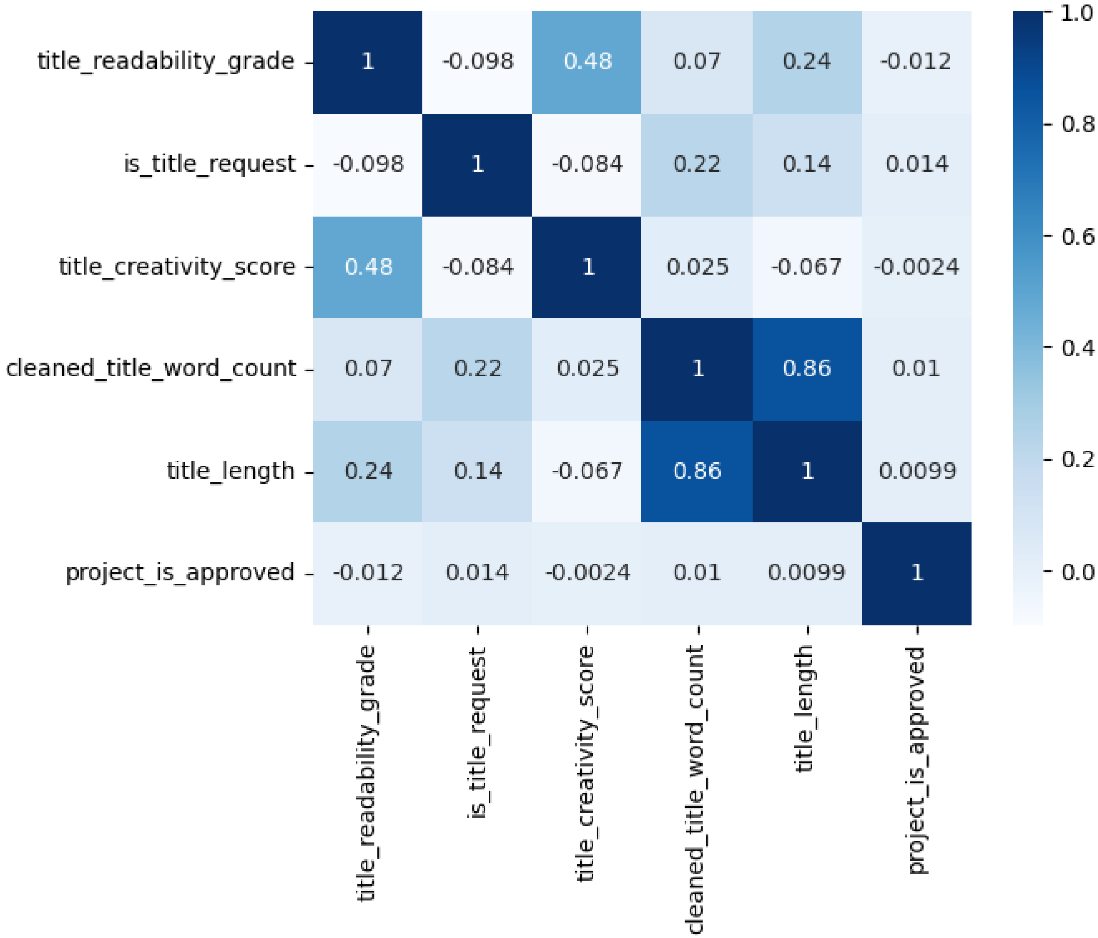
[ ]:
```
        id                                       project_title  \
0  p253737  Educational Support for English Learners at Home
1  p258326              Wanted: Projector for Hungry Learners

   title_readability_grade  is_title_request  title_creativity_score  \
0                    10.74                 1                   1.297
1                     7.60                 0                   2.069

                     cleaned_project_title  cleaned_title_word_count  \
0  educational support english learners home                         5
1           wanted projector hungry learners                         4

   title_length  project_is_approved
0            48                    0
```

```
1            37                      1
```

[ ]:
```python
project_title_df.describe()
```

[ ]:
```
       title_readability_grade  is_title_request  title_creativity_score  \
count            109248.000000     109248.000000           109248.000000
mean                  5.770717          0.088093                1.622230
std                   5.656112          0.283432                0.588561
min                 -14.810000          0.000000                0.000000
25%                   1.313000          0.000000                1.221000
50%                   5.240000          0.000000                1.556000
75%                   9.180000          0.000000                1.945000
max                  55.600000          1.000000                6.100000

       cleaned_title_word_count   title_length  project_is_approved
count             109248.000000  109248.000000        109248.000000
mean                   3.677669      32.464759             0.848583
std                    1.520696      13.418771             0.358456
min                    0.000000       5.000000             0.000000
25%                    2.000000      22.000000             1.000000
50%                    3.000000      30.000000             1.000000
75%                    5.000000      41.000000             1.000000
max                   15.000000     108.000000             1.000000
```

[ ]:
```python
num_cols = project_title_df.select_dtypes(include=np.number)

g = sns.heatmap(num_cols.corr(), cmap='Blues', annot=True)
plt.show()
```

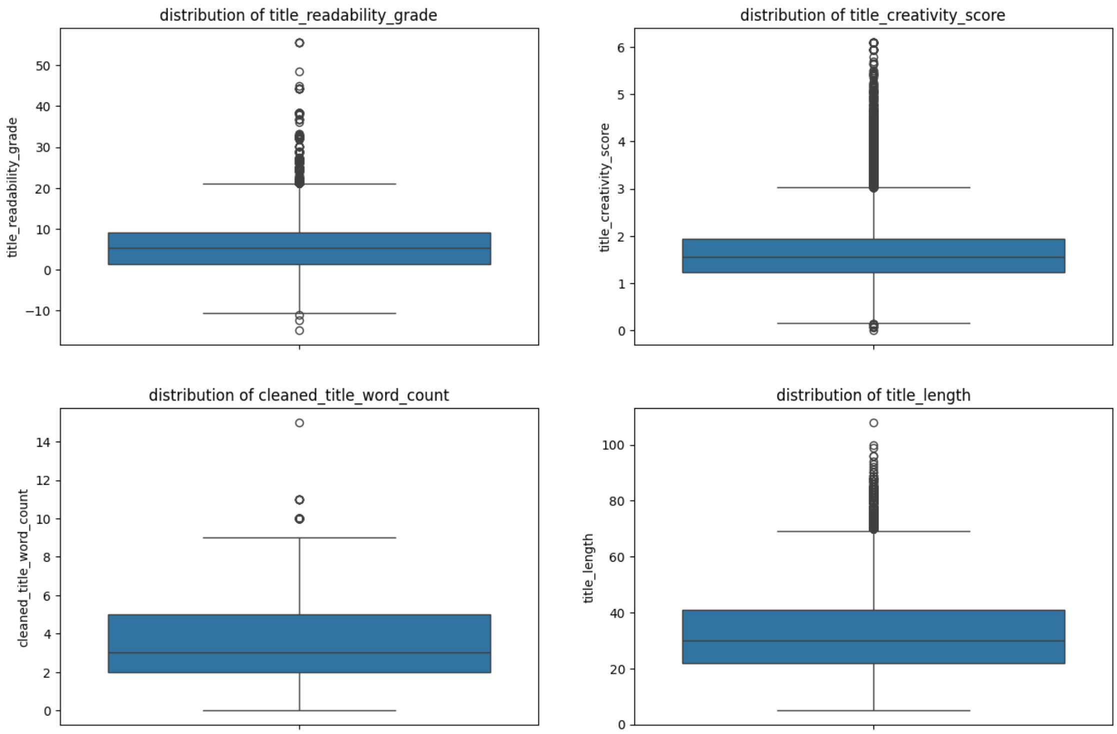



[ ]:
```
project_title_df['is_title_request'].value_counts(normalize=True)
```

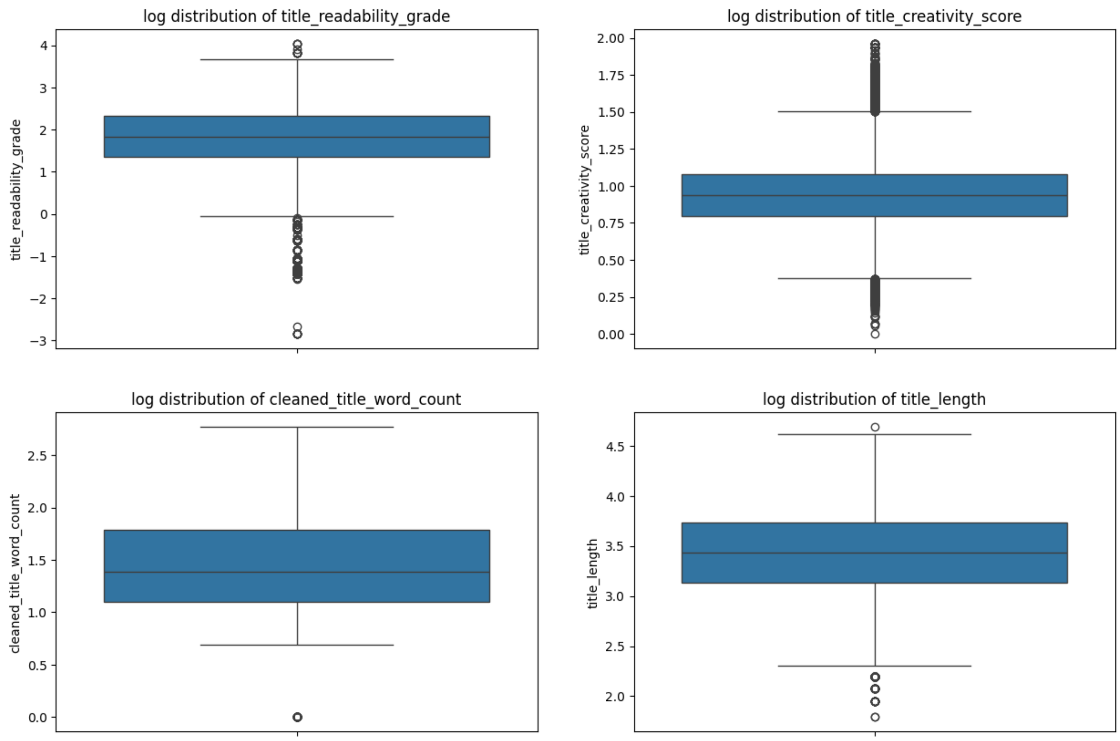
[ ]:
```
is_title_request
0    0.911907
1    0.088093
Name: proportion, dtype: float64
```

[ ]:
```
# distributions of numerical columns
cols = ['title_readability_grade', 'title_creativity_score',␣
 ↪'cleaned_title_word_count', 'title_length']

plt.figure(figsize=(15, 10))
for i, col in enumerate(cols):
  plt.subplot(2, 2, i+1)
  sns.boxplot(data=project_title_df, y=col)
  plt.title('distribution of ' + col)
```

```
plt.show()
```




```
[ ]: # distributions of numerical columns
cols = ['title_readability_grade', 'title_creativity_score',␣
 ↪'cleaned_title_word_count', 'title_length']
log_project_title_df = np.log1p(project_title_df[cols])

plt.figure(figsize=(15, 10))
for i, col in enumerate(cols):
  plt.subplot(2, 2, i+1)
  sns.boxplot(data=log_project_title_df, y=col)
  plt.title('log distribution of ' + col)

plt.show()
```




[ ]:
```
cols = ['title_readability_grade', 'title_creativity_score',␣
↪'cleaned_title_word_count', 'title_length']
res=pd.DataFrame()

for col in cols:
  print(col + 'vs project_is_approved')
  t = ttest(project_title_df, col, 'project_is_approved')
  res = pd.concat([res,t])
  print()

res
```

```
title_readability_gradevs project_is_approved
   project_is_approved  title_readability_grade
0                    0                 5.933517
1                    1                 5.741667

title_creativity_scorevs project_is_approved
   project_is_approved  title_creativity_score
0                    0                 1.62554
1                    1                 1.62164

cleaned_title_word_countvs project_is_approved
   project_is_approved  cleaned_title_word_count
```

```
0                      0                   3.641277
1                      1                   3.684163

title_lengthvs project_is_approved
   project_is_approved  title_length
0                      0     32.150103
1                      1     32.520905
```

[ ]:

```
               numerical_column   categorical_column      means    t_stat  \
0   title_readability_grade  project_is_approved  different  3.864414
0    title_creativity_score  project_is_approved       same  0.776527
0  cleaned_title_word_count  project_is_approved  different -3.342762
0              title_length  project_is_approved  different -3.216104

   p_value variances  levene_stat     levene_p  cohens_d      effect
0  0.000112   unequal    59.200531  1.435802e-14  0.033921  Negligible
0  0.437446   unequal     4.997960  2.537922e-02  0.006626  Negligible
0  0.000831   unequal     4.616947  3.165973e-02 -0.028203  Negligible
0  0.001301   unequal    10.427440  1.241934e-03 -0.027634  Negligible
```

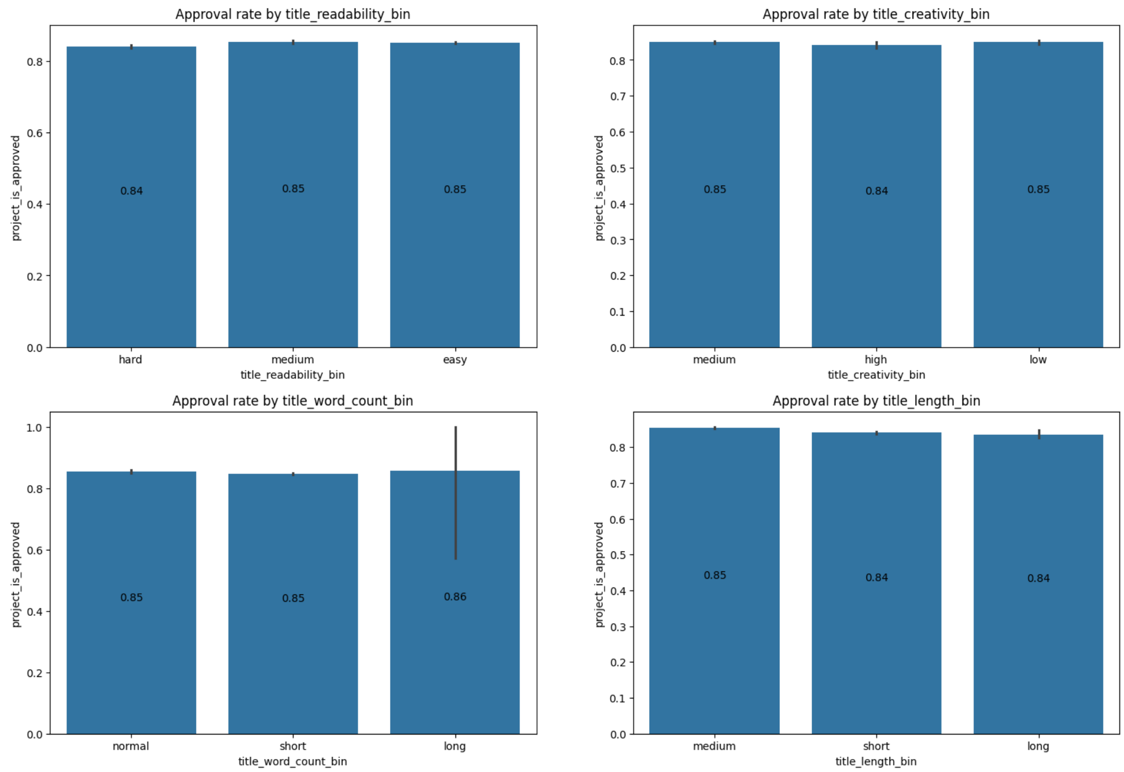
[ ]:

```python
def bin_title_readability(x):
    if x <= 5:
        return "easy"
    elif x <= 9:
        return "medium"
    else:
        return "hard"

def bin_title_creativity(x):
    if x < 1:
        return "low"
    elif x < 2.5:
        return "medium"
    else:
        return "high"

def bin_title_word_count(x):
    if x <= 4:
        return "short"
    elif x <= 10:
        return "normal"
    else:
        return "long"

def bin_title_length(x):
    if x <= 25:
```

```
        return "short"
    elif x <= 60:
        return "medium"
    else:
        return "long"
```

[ ]:
```
project_title_df['title_readability_bin'] =␣
 ↪project_title_df['title_readability_grade'].apply(bin_title_readability)
project_title_df['title_creativity_bin'] =␣
 ↪project_title_df['title_creativity_score'].apply(bin_title_creativity)
project_title_df['title_word_count_bin'] =␣
 ↪project_title_df['cleaned_title_word_count'].apply(bin_title_word_count)
project_title_df['title_length_bin'] = project_title_df['title_length'].
 ↪apply(bin_title_length)
```

[ ]:
```
cols = ['title_readability_bin', 'title_creativity_bin',␣
 ↪'title_word_count_bin', 'title_length_bin']

plt.figure(figsize=(18, 12))
for i, col in enumerate(cols):
  plt.subplot(2, 2, i+1)
  g = sns.barplot(data=project_title_df, x=col, y='project_is_approved')
  for p in g.patches:
    g.text(p.get_x() + p.get_width() /2, p.get_height()/2, round(p.
 ↪get_height(), 2), ha='center', va='bottom')
  plt.title('Approval rate by ' + col)

plt.show()
```




[ ]:
```
cols = ['title_readability_bin', 'title_creativity_bin',␣
↪'title_word_count_bin', 'title_length_bin', 'is_title_request']

chisquare_test(df=project_title_df, columns=cols,␣
↪target_col='project_is_approved')
```

```
project_is_approved        0      1
title_readability_bin
easy                    7846  44643
hard                    4536  23839
medium                  4160  24224

project_is_approved        0      1
title_creativity_bin
high                    1302   6903
low                     2021  11386
medium                 13219  74417

project_is_approved        0      1
title_word_count_bin
long                       1      6
normal                  4199  24558
short                  12342  68142
```

```
project_is_approved     0      1
title_length_bin
long                  634   3223
medium               9654  56590
short                6254  32893

project_is_approved      0      1
is_title_request
0                    15239  84385
1                     1303   8321
```

[ ]:

```
               category       p_value  chi2_stat  \
0  title_readability_bin  1.313186e-05  22.480938
1   title_creativity_bin  1.614821e-01   3.646722
2    title_word_count_bin  1.188502e-02   8.864953
3        title_length_bin  4.876156e-10  42.882987
4        is_title_request  4.690970e-06  20.959495

   project_is_approved_dependent_on_category  cramers_v      effect
0                                          1   0.014345  Negligible
1                                          0   0.005778  Negligible
2                                          1   0.009008  Negligible
3                                          1   0.019812  Negligible
4                                          1   0.013851  Negligible
```

- **Readability:** The average project title has a readability grade level of approximately **5.77**. Title readability is statistically related to approval, but the actual effect size is **negligible**.
- **Length and Word Count:** Project titles average **32.5 characters** and **3.7 words**. Longer titles show a very slight correlation with approval, but statistical testing confirms this effect is also negligible.
- **Formatting Requests:** Approximately **8.8%** of projects are flagged as title requests. While there is a dependency between this flag and approval, the practical impact is minimal.

### 1.5.12 project_essay analysis

[ ]:

```
projects_essay_df = projects_essay_df.merge(df[['id', 'project_is_approved']],␣
 ↪on='id', how='left')
projects_essay_df.head(2)
```

[ ]:

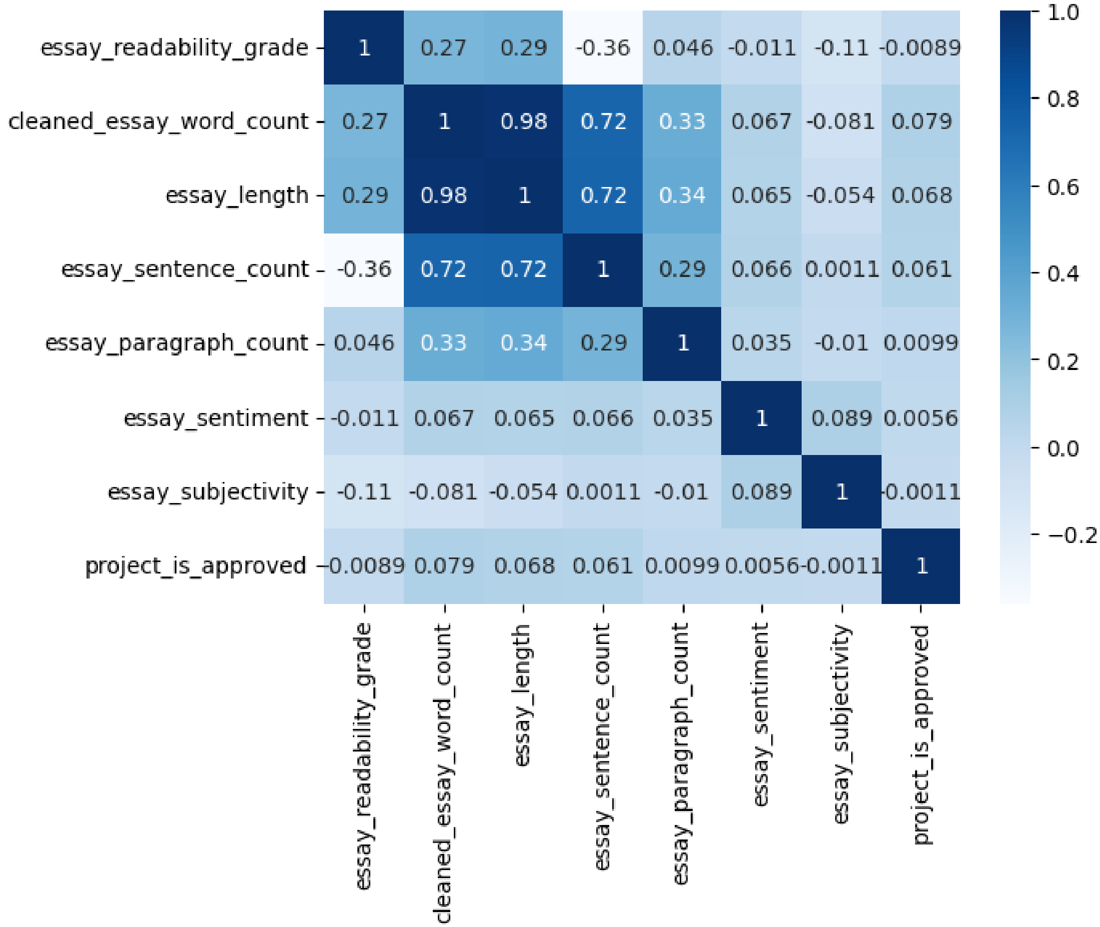
```
        id                                      project_essay  \
0  p253737  My students are English learners that are work…
1  p258326  Our students arrive to our school eager to lea…

                               cleaned_project_essay  essay_readability_grade  \
0  students english learners working english seco…                      9.11
```

```
1  students arrive school eager learn polite gene…                     9.16

   cleaned_essay_word_count  essay_length  essay_sentence_count  \
0                       146          1632                    16
1                        96          1304                    13

   essay_paragraph_count  essay_sentiment  essay_subjectivity  \
0                      4            0.970               0.282
1                      3            0.931               0.412

   project_is_approved
0                    0
1                    1
```

[ ]:
```
projects_essay_df.describe()
```

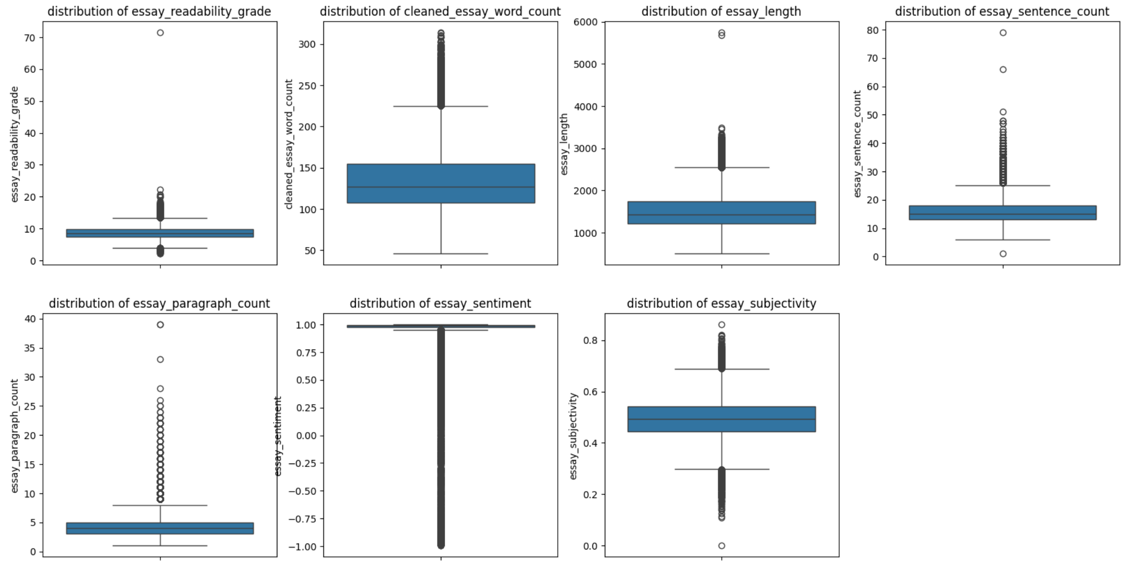
[ ]:
```
       essay_readability_grade  cleaned_essay_word_count   essay_length  \
count            109248.000000             109248.000000  109248.000000
mean                  8.716269                135.789030    1533.225771
std                   1.830200                 35.995066     399.233209
min                   2.130000                 46.000000     505.000000
25%                   7.450000                108.000000    1223.000000
50%                   8.590000                127.000000    1427.000000
75%                   9.830000                155.000000    1752.000000
max                  71.490000                314.000000    5745.000000

       essay_sentence_count  essay_paragraph_count  essay_sentiment  \
count         109248.000000          109248.000000    109248.000000
mean              16.033850               3.735171         0.965946
std                4.166156               1.702970         0.132648
min                1.000000               1.000000        -0.995000
25%               13.000000               3.000000         0.978000
50%               15.000000               4.000000         0.990000
75%               18.000000               5.000000         0.995000
max               79.000000              39.000000         1.000000

       essay_subjectivity  project_is_approved
count       109248.000000        109248.000000
mean             0.492758             0.848583
std              0.074884             0.358456
min              0.000000             0.000000
25%              0.444000             1.000000
50%              0.494000             1.000000
75%              0.542000             1.000000
max              0.861000             1.000000
```

[ ]:
```
num_cols = projects_essay_df.select_dtypes(include=np.number)

g = sns.heatmap(num_cols.corr(), cmap='Blues', annot=True)
plt.show()
```




[ ]:
```
# distributions of numerical columns
cols = ['essay_readability_grade', 'cleaned_essay_word_count', 'essay_length', 
 ↪'essay_sentence_count',        'essay_paragraph_count',        'essay_sentiment',
        'essay_subjectivity']

plt.figure(figsize=(20, 10))
for i, col in enumerate(cols):
  plt.subplot(2, 4, i+1)
  sns.boxplot(data=projects_essay_df, y=col)
  plt.title('distribution of ' + col)
```

```
plt.show()
```




[ ]:
```
cols = ['essay_readability_grade', 'cleaned_essay_word_count', 'essay_length',
    ↪'essay_sentence_count',        'essay_paragraph_count',        'essay_sentiment',
        'essay_subjectivity']

res=pd.DataFrame()

for col in cols:
  print(col + 'vs project_is_approved')
  t = ttest(projects_essay_df, col, 'project_is_approved')
  res = pd.concat([res,t])
  print()

res
```

```
essay_readability_gradevs project_is_approved
   project_is_approved  essay_readability_grade
0                    0                 8.754856
1                    1                 8.709384

cleaned_essay_word_countvs project_is_approved
   project_is_approved  cleaned_essay_word_count
0                    0                129.071334
1                    1                136.987703

essay_lengthvs project_is_approved
```

```
   project_is_approved  essay_length
0                    0   1468.640672
1                    1   1544.750016

essay_sentence_countvs project_is_approved
   project_is_approved  essay_sentence_count
0                    0             15.428727
1                    1             16.141825

essay_paragraph_countvs project_is_approved
   project_is_approved  essay_paragraph_count
0                    0               3.695140
1                    1               3.742314

essay_sentimentvs project_is_approved
   project_is_approved  essay_sentiment
0                    0         0.964179
1                    1         0.966261

essay_subjectivityvs project_is_approved
   project_is_approved  essay_subjectivity
0                    0            0.492952
1                    1            0.492724
```

[ ]:

```
            numerical_column   categorical_column      means      t_stat  \
0   essay_readability_grade  project_is_approved  different    2.782825
0  cleaned_essay_word_count  project_is_approved  different  -27.778967
0              essay_length  project_is_approved  different  -24.125502
0      essay_sentence_count  project_is_approved  different  -21.105795
0     essay_paragraph_count  project_is_approved  different   -3.046765
0           essay_sentiment  project_is_approved       same   -1.860214
0        essay_subjectivity  project_is_approved       same    0.352736

         p_value variances  levene_stat      levene_p  cohens_d      effect
0   5.393418e-03   unequal    54.383154  1.661320e-13  0.024846  Negligible
0  3.329626e-167   unequal   250.629103  2.188366e-56 -0.220615        Weak
0  4.287875e-127   unequal   269.830854  1.460664e-60 -0.191085        Weak
0   5.655032e-98   unequal    83.949852  5.159293e-20 -0.171487        Weak
0   2.315978e-03   unequal    66.449047  3.628104e-16 -0.027703  Negligible
0   6.285799e-02     equal     2.893111  8.896186e-02 -0.015701  Negligible
0   7.242899e-01   unequal    28.534327  9.223544e-08  0.003056  Negligible
```

[ ]:

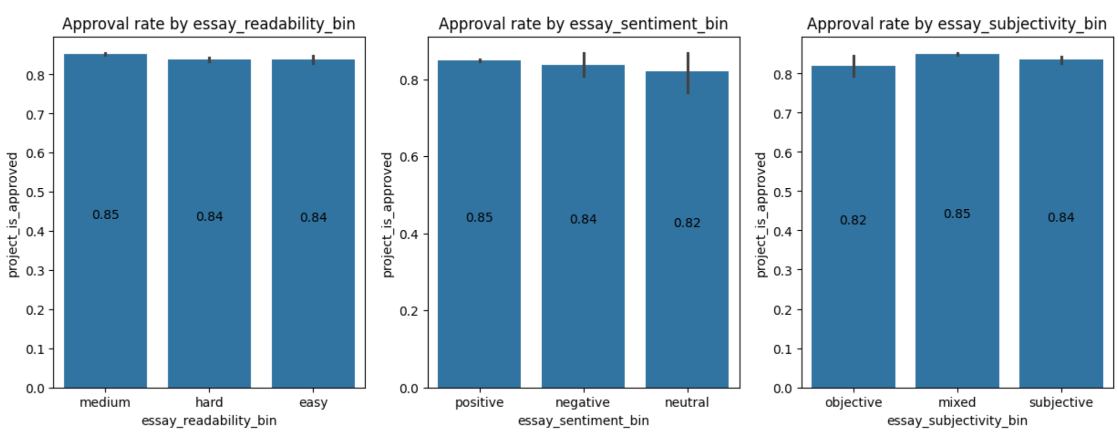
```
def bin_essay_readability(x):
    if x <= 6:
        return "easy"
    elif x <= 10:
```

```python
        return "medium"
    else:
        return "hard"

def bin_essay_word_count(x):
    if x < 100:
        return "short"
    elif x <= 300:
        return "medium"
    else:
        return "long"

def bin_essay_length(x):
    if x < 600:
        return "short"
    elif x <= 1800:
        return "medium"
    else:
        return "long"

def bin_essay_sentence_count(x):
    if x <= 4:
        return "few"
    elif x <= 10:
        return "moderate"
    else:
        return "many"

def bin_essay_paragraph_count(x):
    if x <= 2:
        return "low"
    elif x <= 4:
        return "normal"
    else:
        return "high"

def bin_essay_sentiment(x):
    if x <= -0.2:
        return "negative"
    elif x < 0.2:
        return "neutral"
    else:
        return "positive"

def bin_essay_subjectivity(x):
    if x < 0.3:
        return "objective"
```

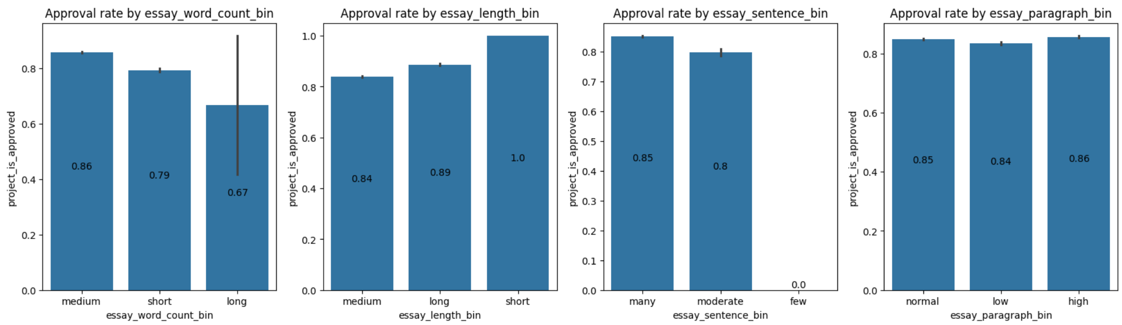
```
    elif x < 0.6:
        return "mixed"
    else:
        return "subjective"
```

[ ]:
```
projects_essay_df['essay_readability_bin'] =␣
 ↪projects_essay_df['essay_readability_grade'].apply(bin_essay_readability)
projects_essay_df['essay_word_count_bin'] =␣
 ↪projects_essay_df['cleaned_essay_word_count'].apply(bin_essay_word_count)
projects_essay_df['essay_length_bin'] = projects_essay_df['essay_length'].
 ↪apply(bin_essay_length)
projects_essay_df['essay_sentence_bin'] =␣
 ↪projects_essay_df['essay_sentence_count'].apply(bin_essay_sentence_count)
projects_essay_df['essay_paragraph_bin'] =␣
 ↪projects_essay_df['essay_paragraph_count'].apply(bin_essay_paragraph_count)
projects_essay_df['essay_sentiment_bin'] = projects_essay_df['essay_sentiment'].
 ↪apply(bin_essay_sentiment)
projects_essay_df['essay_subjectivity_bin'] =␣
 ↪projects_essay_df['essay_subjectivity'].apply(bin_essay_subjectivity)
```

[ ]:
```
cols = ['essay_readability_bin', 'essay_sentiment_bin',␣
 ↪'essay_subjectivity_bin']

plt.figure(figsize=(15, 5))
for i, col in enumerate(cols):
  plt.subplot(1, 3, i+1)
  g = sns.barplot(data=projects_essay_df, x=col, y='project_is_approved')
  for p in g.patches:
    g.text(p.get_x() + p.get_width() /2, p.get_height()/2, round(p.
 ↪get_height(), 2), ha='center', va='bottom')
  plt.title('Approval rate by ' + col)

plt.show()
```



[ ]:
```
cols = ['essay_word_count_bin', 'essay_length_bin',
        'essay_sentence_bin',        'essay_paragraph_bin']

plt.figure(figsize=(20, 5))
for i, col in enumerate(cols):
  plt.subplot(1, 4, i+1)
  g = sns.barplot(data=projects_essay_df, x=col, y='project_is_approved')
  for p in g.patches:
    g.text(p.get_x() + p.get_width() /2, p.get_height()/2, round(p.
↪get_height(), 2), ha='center', va='bottom')
  plt.title('Approval rate by ' + col)

plt.show()
```




[ ]:
```
cols = ['essay_readability_bin', 'essay_sentiment_bin',␣
↪'essay_subjectivity_bin',
        'essay_word_count_bin', 'essay_length_bin',
        'essay_sentence_bin',        'essay_paragraph_bin']

chisquare_test(df=projects_essay_df, columns=cols,␣
↪target_col='project_is_approved')
```

```
project_is_approved        0      1
essay_readability_bin
easy                     935   4837
hard                    3907  20369
medium                 11700  67500

project_is_approved      0      1
essay_sentiment_bin
negative                83    431
neutral                 41    187
positive             16418  92088
```

```
project_is_approved        0      1
essay_subjectivity_bin
mixed                  15086  85412
objective                144    652
subjective              1312   6642

project_is_approved      0      1
essay_word_count_bin
long                     4      8
medium               13995  82983
short                 2543   9715

project_is_approved      0      1
essay_length_bin
long                  2783  21539
medium               13759  71165
short                    0      2

project_is_approved      0      1
essay_sentence_bin
few                      1      0
many                 15635  89140
moderate               906   3566

project_is_approved     0      1
essay_paragraph_bin
high                 4613  27658
low                  3739  18976
normal               8190  46072
```

[ ]:
```
                 category       p_value   chi2_stat  \
0   essay_readability_bin  2.324436e-07   30.549236
1     essay_sentiment_bin  3.971893e-01    1.846685
2  essay_subjectivity_bin  1.202198e-04   18.052378
3    essay_word_count_bin  9.923771e-75  340.797898
4        essay_length_bin  3.535518e-73  333.651704
5      essay_sentence_bin  1.373406e-22  100.679157
6     essay_paragraph_bin  2.445279e-11   48.868554

   project_is_approved_dependent_on_category  cramers_v      effect
0                                          1   0.016722  Negligible
1                                          0   0.004111  Negligible
2                                          1   0.012855  Negligible
3                                          1   0.055852  Negligible
4                                          1   0.055264  Negligible
```

```
5                                            1   0.030357  Negligible
6                                            1   0.021150  Negligible
```

- **Length Matters:** Approved projects generally feature longer essays; statistical testing confirms a significant difference ($p < 0.05$) in word counts between approved and rejected proposals.
- **Readability Trends:** High-performing projects often feature **"medium"** readability levels, and while harder-to-read essays have a statistically significant relationship to approval, the effect size is **negligible**.
- **Sentiment:** Nearly all essays maintain a highly **positive sentiment** (mean ~0.966), making it a poor differentiator for success since nearly all teachers use an asset-framed, optimistic tone.
- **Inverted-U Effect:** Research indicates that while more information is good, excessive word counts can eventually lead to a "burden of understanding" for donors, suggesting an optimal length for narratives.

## 1.6 Model Training

[47]:
```
# import numpy as np
# import pandas as pd
# import matplotlib.pyplot as plt
# import seaborn as sns
# import warnings
# warnings.filterwarnings('ignore')

# !gdown 15_ylYp27G-tjpXmusKQec7R9saX-_YqM    # resources_preprocessed.csv
# !gdown 1d-nscAgfP4nyFWD228nF9SPdePrQFPTT    # projects_preprocessed.csv

# !gdown 1wFsGAqpz1-6yuVbCwlCqdjmJgfzI7eVy    # project_title_df_final.csv
# !gdown 16P1eplRd1m5jnFOAF_g7pszbfqp2LAiB    # projects_essay_df_final.csv

# !gdown 1TtPCF4qtTDptyF3Ha37davRHxkE4w-Wo    # merged_final.csv

# !gdown 1Szicd-q1NmzkKR7ty8-dJSGAyt9RhW3L    # proj_cat.csv
# !gdown 1QxV4562s8iRAqGuY49_F8IeDFSczzezd    # proj_sub_cat.csv
# !gdown 1pqbVrxrm5RByHeXj5rpm36gOHPWjiIyN    # resource_cluster_agg.csv


# resources = pd.read_csv('/content/resources_preprocessed.csv')
# projects = pd.read_csv('/content/projects_preprocessed.csv')

# project_title_df = pd.read_csv('/content/project_title_df_final.csv')
# projects_essay_df = pd.read_csv('/content/projects_essay_df_final.csv')

# df = pd.read_csv('/content/merged_final.csv')

# proj_cat = pd.read_csv('/content/proj_cat.csv')
```

```python
# proj_sub_cat = pd.read_csv('/content/proj_sub_cat.csv')
# resource_cluster_agg = pd.read_csv('/content/resource_cluster_agg.csv')

# resources.fillna('', inplace=True)
# projects.fillna('', inplace=True)
# project_title_df.fillna('', inplace=True)
# projects_essay_df.fillna('', inplace=True)
# df.fillna('', inplace=True)
# proj_cat.fillna('', inplace=True)
# proj_sub_cat.fillna('', inplace=True)
# resource_cluster_agg.fillna('', inplace=True)

# projects["project_submitted_datetime"] = pd.to_datetime(
#     projects["project_submitted_datetime"], format="%Y-%m-%d %H:%M:%S"
# )
```

[2]:
```python
df.columns
```

[2]:
```
Index(['id', 'teacher_id', 'teacher_prefix', 'school_state',
       'project_grade_category', 'project_subject_categories',
       'project_subject_subcategories', 'project_title',
       'teacher_number_of_previously_posted_projects', 'project_is_approved',
       'project_essay', 'Books', 'Classroom_aid', 'Electronics', 'Food',
       'Other', 'STEM', 'Sports_Fitness', 'Stationery', 'Subscriptions',
       'total_resource_cost', 'project_submitted_date',
       'project_submission_year', 'project_submission_month',
       'project_submission_day', 'project_submission_hour',
       'teacher_experience', 'project_cost_bin', 'total_resources_quantity',
       'project_qty_bin'],
      dtype='object')
```

[3]:
```python
df_cols = ['id', 'teacher_id', 'teacher_prefix', 'school_state',
           'project_grade_category', 'project_is_approved',
           'teacher_number_of_previously_posted_projects',
           'Books', 'Classroom_aid', 'Electronics', 'Food', 'Other', 'STEM',
           'Sports_Fitness', 'Stationery', 'Subscriptions',
           'total_resource_cost', 'project_submission_year',
           'project_submission_month', 'project_submission_day',
           'project_submission_hour']
```

[4]:
```python
project_title_df.columns
```

[4]:
```
Index(['id', 'project_title', 'title_readability_grade', 'is_title_request',
       'title_creativity_score', 'cleaned_project_title',
       'cleaned_title_word_count', 'title_length', 'project_is_approved',
       'title_readability_bin', 'title_creativity_bin', 'title_word_count_bin',
       'title_length_bin'],
```

```
       dtype='object')
```

[5]:
```
project_title_df_cols = ['id', 'project_title', 'title_readability_grade',
                         'is_title_request', 'title_creativity_score',
                         'cleaned_title_word_count', 'title_length']
```

[6]:
```
projects_essay_df.columns
```

[6]:
```
Index(['id', 'project_essay', 'cleaned_project_essay',
       'essay_readability_grade', 'cleaned_essay_word_count', 'essay_length',
       'essay_sentence_count', 'essay_paragraph_count', 'essay_sentiment',
       'essay_subjectivity', 'project_is_approved', 'essay_readability_bin',
       'essay_word_count_bin', 'essay_length_bin', 'essay_sentence_bin',
       'essay_paragraph_bin', 'essay_sentiment_bin', 'essay_subjectivity_bin'],
      dtype='object')
```

[7]:
```
projects_essay_df_cols = ['id', 'project_essay','essay_readability_grade',
                          'cleaned_essay_word_count', 'essay_length',
                          'essay_sentence_count', 'essay_paragraph_count',
                          'essay_sentiment', 'essay_subjectivity']
```

[8]:
```
proj_sub_cat['id'] = df['id']
proj_sub_cat.columns
```

[8]:
```
Index(['Applied Sciences', 'Care & Hunger', 'Character Education',
       'Civics & Government', 'College & Career Prep', 'Community Service',
       'ESL', 'Early Development', 'Economics', 'Environmental Science',
       'Extracurricular', 'Financial Literacy', 'Foreign Languages',
       'Gym & Fitness', 'Health & Life Science', 'Health & Wellness',
       'History & Geography', 'Literacy', 'Literature & Writing',
       'Mathematics', 'Music', 'Nutrition Education', 'Other',
       'Parent Involvement', 'Performing Arts', 'Social Sciences',
       'Special Needs', 'Team Sports', 'Visual Arts', 'Warmth',
       'approval_status', 'total_project_cost', 'id'],
      dtype='object')
```

[9]:
```
proj_sub_cat_cols = ['id', 'Applied Sciences', 'Care & Hunger',
                     'Character Education', 'Civics & Government',
                     'College & Career Prep', 'Community Service', 'ESL',
                     'Early Development', 'Economics', 'Environmental Science',
                     'Extracurricular', 'Financial Literacy',
                     'Foreign Languages', 'Gym & Fitness',
                     'Health & Life Science', 'Health & Wellness',
                     'History & Geography', 'Literacy', 'Literature & Writing',
                     'Mathematics', 'Music', 'Nutrition Education', 'Other',
                     'Parent Involvement', 'Performing Arts', 'Social Sciences',
                     'Special Needs', 'Team Sports', 'Visual Arts', 'Warmth']
```

[10]:
```
df_final = pd.merge(df[df_cols], project_title_df[project_title_df_cols],
                    how='inner', on='id')
df_final.drop(columns=['Other'], inplace=True)

df_final = pd.merge(df_final, projects_essay_df[projects_essay_df_cols],
                    how='inner', on='id')

df_final = pd.merge(df_final, proj_sub_cat[proj_sub_cat_cols],
                    how='inner', on='id')
df_final.rename(columns={'Other': 'Other_Category'}, inplace=True)
```

[11]:
```
df_final.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 109248 entries, 0 to 109247
Data columns (total 64 columns):
 #   Column                                        Non-Null Count   Dtype
---  ------                                        --------------   -----
 0   id                                            109248 non-null  object
 1   teacher_id                                    109248 non-null  object
 2   teacher_prefix                                109248 non-null  object
 3   school_state                                  109248 non-null  object
 4   project_grade_category                        109248 non-null  object
 5   project_is_approved                           109248 non-null  int64
 6   teacher_number_of_previously_posted_projects  109248 non-null  int64
 7   Books                                         109248 non-null  int64
 8   Classroom_aid                                 109248 non-null  int64
 9   Electronics                                   109248 non-null  int64
 10  Food                                          109248 non-null  int64
 11  STEM                                          109248 non-null  int64
 12  Sports_Fitness                                109248 non-null  int64
 13  Stationery                                    109248 non-null  int64
 14  Subscriptions                                 109248 non-null  int64
 15  total_resource_cost                           109248 non-null  float64
 16  project_submission_year                       109248 non-null  int64
 17  project_submission_month                      109248 non-null  object
 18  project_submission_day                        109248 non-null  object
 19  project_submission_hour                       109248 non-null  int64
 20  project_title                                 109248 non-null  object
 21  title_readability_grade                       109248 non-null  float64
 22  is_title_request                              109248 non-null  int64
 23  title_creativity_score                        109248 non-null  float64
 24  cleaned_title_word_count                      109248 non-null  int64
 25  title_length                                  109248 non-null  int64
 26  project_essay                                 109248 non-null  object
 27  essay_readability_grade                       109248 non-null  float64
 28  cleaned_essay_word_count                      109248 non-null  int64
```

```
 29  essay_length                                      109248 non-null  int64
 30  essay_sentence_count                              109248 non-null  int64
 31  essay_paragraph_count                             109248 non-null  int64
 32  essay_sentiment                                   109248 non-null  float64
 33  essay_subjectivity                                109248 non-null  float64
 34  Applied Sciences                                  109248 non-null  int64
 35  Care & Hunger                                     109248 non-null  int64
 36  Character Education                               109248 non-null  int64
 37  Civics & Government                               109248 non-null  int64
 38  College & Career Prep                             109248 non-null  int64
 39  Community Service                                 109248 non-null  int64
 40  ESL                                               109248 non-null  int64
 41  Early Development                                 109248 non-null  int64
 42  Economics                                         109248 non-null  int64
 43  Environmental Science                             109248 non-null  int64
 44  Extracurricular                                   109248 non-null  int64
 45  Financial Literacy                                109248 non-null  int64
 46  Foreign Languages                                 109248 non-null  int64
 47  Gym & Fitness                                     109248 non-null  int64
 48  Health & Life Science                             109248 non-null  int64
 49  Health & Wellness                                 109248 non-null  int64
 50  History & Geography                               109248 non-null  int64
 51  Literacy                                          109248 non-null  int64
 52  Literature & Writing                              109248 non-null  int64
 53  Mathematics                                       109248 non-null  int64
 54  Music                                             109248 non-null  int64
 55  Nutrition Education                               109248 non-null  int64
 56  Other_Category                                    109248 non-null  int64
 57  Parent Involvement                                109248 non-null  int64
 58  Performing Arts                                   109248 non-null  int64
 59  Social Sciences                                   109248 non-null  int64
 60  Special Needs                                     109248 non-null  int64
 61  Team Sports                                       109248 non-null  int64
 62  Visual Arts                                       109248 non-null  int64
 63  Warmth                                            109248 non-null  int64
dtypes: float64(6), int64(49), object(9)
memory usage: 53.3+ MB
```

### 1.6.1 Train test split

[12]:
```
from sklearn.model_selection import train_test_split

X = df_final.drop(columns=['project_is_approved'])
y = df_final['project_is_approved']

# Step 1: Train (60%) + Temp (40%)
X_train, X_temp, y_train, y_temp = train_test_split(
```

```
    X, y,
    test_size=0.40,
    stratify=y,
    random_state=42
)

# Step 2: Validation (20%) + Test (20%)
X_val, X_test, y_val, y_test = train_test_split(
    X_temp, y_temp,
    test_size=0.50,
    stratify=y_temp,
    random_state=42
)
```

### 1.6.2 Feature Encoding

**Target encoding for teacher_id and school_state**

[13]:
```
from sklearn.model_selection import StratifiedKFold
import pandas as pd

def kfold_target_encode(X_train, y_train, X_val, X_test, column, n_splits=5,␣
 ↪smoothing=1):

    skf = StratifiedKFold(n_splits=n_splits, shuffle=True, random_state=42)
    global_mean = y_train.mean()

    train_encoded = pd.Series(index=X_train.index, dtype=float)

    # ---------- OOF encoding for TRAIN ----------
    for tr_idx, val_idx in skf.split(X_train, y_train):
        X_tr = X_train.iloc[tr_idx]
        y_tr = y_train.iloc[tr_idx]
        X_val_fold = X_train.iloc[val_idx]

        stats = (
            pd.DataFrame({
                "mean": y_tr.groupby(X_tr[column]).mean(),
                "count": X_tr[column].value_counts()
            })
        )

        stats["enc"] = (
            (stats["mean"] * stats["count"] + global_mean * smoothing) /
            (stats["count"] + smoothing)
        )

        train_encoded.iloc[val_idx] = X_val_fold[column].map(stats["enc"])
```

```python
    train_encoded.fillna(global_mean, inplace=True)

    # ---------- FULL TRAIN → VAL & TEST ----------
    full_stats = pd.DataFrame({
        "mean": y_train.groupby(X_train[column]).mean(),
        "count": X_train[column].value_counts()
    })

    full_stats["enc"] = (
        (full_stats["mean"] * full_stats["count"] + global_mean * smoothing) /
        (full_stats["count"] + smoothing)
    )

    val_encoded = X_val[column].map(full_stats["enc"]).fillna(global_mean)
    test_encoded = X_test[column].map(full_stats["enc"]).fillna(global_mean)

    return train_encoded, val_encoded, test_encoded
```

[14]:
```python
# saving this model for api development
import joblib

global_mean = y_train.mean()

teacher_map = (
    y_train
    .groupby(X_train['teacher_id'])
    .mean()
    .to_dict()
)

state_map = (
    y_train
    .groupby(X_train['school_state'])
    .mean()
    .to_dict()
)

joblib.dump(
    {"mapping": teacher_map, "global_mean": global_mean}, "teacher_id_te.pkl"
)

joblib.dump(
    {"mapping": state_map, "global_mean": global_mean}, "school_state_te.pkl"
)
```

[14]: ['school_state_te.pkl']

[15]:
```
X_train['teacher_id'], X_val['teacher_id'], X_test['teacher_id'] = (
    kfold_target_encode(
        X_train=X_train,
        y_train=y_train,
        X_val=X_val,
        X_test=X_test,
        column='teacher_id',
        smoothing=10      # high-cardinality → more smoothing
    )
)
```

[16]:
```
X_train['school_state'], X_val['school_state'], X_test['school_state'] = (
    kfold_target_encode(
        X_train=X_train,
        y_train=y_train,
        X_val=X_val,
        X_test=X_test,
        column='school_state',
        smoothing=1      # low-cardinality → light smoothing
    )
)
```

- Due to high cardinality of teacher_id and school_state, normal target encoding will cause data leakage and hench we can use Stratified Kfold.

**One Hot Encoding for teacher_prefix and project_grade_category**

[17]:
```
from sklearn.preprocessing import OneHotEncoder
cat_cols = ['teacher_prefix', 'project_grade_category']

ohe = OneHotEncoder(handle_unknown='ignore', sparse_output=False)
ohe.fit(X_train[cat_cols])
```

[17]:
```
OneHotEncoder(handle_unknown='ignore', sparse_output=False)
```

[18]:
```
ohe.get_feature_names_out(cat_cols)
```

[18]:
```
array(['teacher_prefix_Dr.', 'teacher_prefix_Mr.', 'teacher_prefix_Mrs.',
       'teacher_prefix_Ms.', 'teacher_prefix_Teacher',
       'project_grade_category_Grades 3-5',
       'project_grade_category_Grades 6-8',
       'project_grade_category_Grades 9-12',
       'project_grade_category_Grades PreK-2'], dtype=object)
```

[19]:
```
# saving model
joblib.dump(ohe, "ohe_encoder.pkl")
```

[19]:
```
['ohe_encoder.pkl']
```

[20]:
```
# transform
train_ohe = ohe.transform(X_train[cat_cols])
val_ohe   = ohe.transform(X_val[cat_cols])
test_ohe  = ohe.transform(X_test[cat_cols])

# column names
ohe_cols = ohe.get_feature_names_out(cat_cols)

# to DataFrame
train_ohe_df = pd.DataFrame(train_ohe, columns=ohe_cols, index=X_train.index)
val_ohe_df   = pd.DataFrame(val_ohe,   columns=ohe_cols, index=X_val.index)
test_ohe_df  = pd.DataFrame(test_ohe,  columns=ohe_cols, index=X_test.index)

# concat back
X_train = pd.concat([X_train.drop(columns=cat_cols), train_ohe_df], axis=1)
X_val   = pd.concat([X_val.drop(columns=cat_cols),   val_ohe_df], axis=1)
X_test  = pd.concat([X_test.drop(columns=cat_cols),  test_ohe_df], axis=1)
```

- Using one hot encoding for low cardinal catefories teacher_prefix and project_grade_category

**project_submission_month and project_submission_day**

[21]:
```
month_mapping = {
    'January': 1, 'February': 2, 'March': 3, 'April': 4,
    'May': 5, 'June': 6, 'July': 7, 'August': 8,
    'September': 9, 'October': 10, 'November': 11, 'December': 12
}

# Convert month name to month number
X_train['project_submission_month'] = X_train['project_submission_month'].
 ↪map(month_mapping)
X_val['project_submission_month'] = X_val['project_submission_month'].
 ↪map(month_mapping)
X_test['project_submission_month'] = X_test['project_submission_month'].
 ↪map(month_mapping)
```

[22]:
```
day_mapping = {
    'Monday': 0, 'Tuesday': 1, 'Wednesday': 2, 'Thursday': 3, 'Friday': 4,
    'Saturday': 5, 'Sunday': 6
}

# Map the string day names to numerical values
X_train['project_submission_day'] = X_train['project_submission_day'].
 ↪map(day_mapping)
X_val['project_submission_day'] = X_val['project_submission_day'].
 ↪map(day_mapping)
```

```
X_test['project_submission_day'] = X_test['project_submission_day'].
    ↪map(day_mapping)
```

**log transformation for right skewed numerical columns**

[23]:
```
num_log_cols = ['teacher_number_of_previously_posted_projects',
                'total_resource_cost', 'title_readability_grade',
                'title_creativity_score', 'cleaned_title_word_count',
                'title_length', 'essay_readability_grade', 'essay_length',
                'cleaned_essay_word_count', 'essay_paragraph_count',
                'essay_sentence_count', 'essay_sentiment', 'essay_subjectivity']

for col in num_log_cols:
  X_train[col] = np.log1p(X_train[col])
  X_val[col] = np.log1p(X_val[col])
  X_test[col] = np.log1p(X_test[col])
```

**SBERT embeddings for project_title and project_essay**

[24]:
```
from sentence_transformers import SentenceTransformer

sbert = SentenceTransformer('all-MiniLM-L6-v2')
```

```
modules.json:   0%|          | 0.00/349 [00:00<?, ?B/s]

config_sentence_transformers.json:   0%|          | 0.00/116 [00:00<?, ?B/s]

README.md: 0.00B [00:00, ?B/s]

sentence_bert_config.json:   0%|          | 0.00/53.0 [00:00<?, ?B/s]

config.json:   0%|          | 0.00/612 [00:00<?, ?B/s]

model.safetensors:   0%|          | 0.00/90.9M [00:00<?, ?B/s]

tokenizer_config.json:   0%|          | 0.00/350 [00:00<?, ?B/s]

vocab.txt: 0.00B [00:00, ?B/s]

tokenizer.json: 0.00B [00:00, ?B/s]

special_tokens_map.json:   0%|          | 0.00/112 [00:00<?, ?B/s]

config.json:   0%|          | 0.00/190 [00:00<?, ?B/s]
```

[25]:
```
# Convert to list for SBERT
titles_train = X_train['project_title'].tolist()
essays_train = X_train['project_essay'].tolist()

titles_val = X_val['project_title'].tolist()
essays_val = X_val['project_essay'].tolist()

titles_test = X_test['project_title'].tolist()
```

```
essays_test = X_test['project_essay'].tolist()
```

[26]:
```
# Train embeddings
title_emb_train = sbert.encode(titles_train, batch_size=64,␣
↪show_progress_bar=True)
essay_emb_train = sbert.encode(essays_train, batch_size=64,␣
↪show_progress_bar=True)

# Validation embeddings
title_emb_val = sbert.encode(titles_val, batch_size=64, show_progress_bar=True)
essay_emb_val = sbert.encode(essays_val, batch_size=64, show_progress_bar=True)

# Test embeddings
title_emb_test = sbert.encode(titles_test, batch_size=64,␣
↪show_progress_bar=True)
essay_emb_test = sbert.encode(essays_test, batch_size=64,␣
↪show_progress_bar=True)
```

```
Batches:   0%|          | 0/1025 [00:00<?, ?it/s]

Batches:   0%|          | 0/1025 [00:00<?, ?it/s]

Batches:   0%|          | 0/342 [00:00<?, ?it/s]

Batches:   0%|          | 0/342 [00:00<?, ?it/s]

Batches:   0%|          | 0/342 [00:00<?, ?it/s]

Batches:   0%|          | 0/342 [00:00<?, ?it/s]
```

[27]:
```
# train
title_emb_train_df = pd.DataFrame(title_emb_train,
                                  index=X_train.index,
                                  columns=[f"title_emb_{i}" for i in␣
↪range(384)])

essay_emb_train_df = pd.DataFrame(essay_emb_train,
                                  index=X_train.index,
                                  columns=[f"essay_emb_{i}" for i in␣
↪range(384)])

# validation
title_emb_val_df = pd.DataFrame(title_emb_val,
                                index=X_val.index,
                                columns=[f"title_emb_{i}" for i in range(384)])

essay_emb_val_df = pd.DataFrame(essay_emb_val,
                                index=X_val.index,
                                columns=[f"essay_emb_{i}" for i in range(384)])
```

```
# test
title_emb_test_df = pd.DataFrame(title_emb_test,
                                 index=X_test.index,
                                 columns=[f"title_emb_{i}" for i in range(384)])

essay_emb_test_df = pd.DataFrame(essay_emb_test,
                                 index=X_test.index,
                                 columns=[f"essay_emb_{i}" for i in range(384)])
```

[28]:
```
# concatenate embeddings
X_train = pd.concat([X_train.reset_index(drop=True),
                     title_emb_train_df.reset_index(drop=True),
                     essay_emb_train_df.reset_index(drop=True)], axis=1)

X_val = pd.concat([X_val.reset_index(drop=True),
                   title_emb_val_df.reset_index(drop=True),
                   essay_emb_val_df.reset_index(drop=True)], axis=1)


X_test = pd.concat([X_test.reset_index(drop=True),
                    title_emb_test_df.reset_index(drop=True),
                    essay_emb_test_df.reset_index(drop=True)], axis=1)

# drop columns
X_train.drop(columns=['id', 'project_title', 'project_essay'], inplace=True)
X_val.drop(columns=['id','project_title', 'project_essay'], inplace=True)
X_test.drop(columns=['id','project_title', 'project_essay'], inplace=True)
```

### 1.6.3 Model Fitting

[ ]:
```
!pip install optuna --quiet
```

[ ]:
```
# class weight for handling class imbalance
pos = y_train.sum()
neg = len(y_train) - pos
class_weight = neg / pos
class_weight
```

[ ]:
```
np.float64(0.17843338187440447)
```

[ ]:
```
import optuna
import xgboost as xgb
from sklearn.metrics import average_precision_score

# define the Optuna objective function
```

```python
def objective(trial):

    params = {
        "objective": "binary:logistic",
        "eval_metric": "auc",          # checks auc-roc for early stopping
        "tree_method": "hist",
        "random_state": 42,
        "device": "cuda",
        "early_stopping_rounds": 50,

        # core params
        "n_estimators": trial.suggest_int("n_estimators", 300, 900),
        "max_depth": trial.suggest_int("max_depth", 3, 7),
        "learning_rate": trial.suggest_float("learning_rate", 0.01, 0.1,␣
 ↪log=True),

        # sampling
        "subsample": trial.suggest_float("subsample", 0.6, 1.0),
        "colsample_bytree": trial.suggest_float("colsample_bytree", 0.5, 1.0),

        # regularization
        "min_child_weight": trial.suggest_int("min_child_weight", 1, 10),
        "gamma": trial.suggest_float("gamma", 0.0, 0.3),
        "reg_alpha": trial.suggest_float("reg_alpha", 0.0, 1.0),
        "reg_lambda": trial.suggest_float("reg_lambda", 0.0, 1.0),

        # imbalance handling
        "scale_pos_weight": class_weight
    }

    model = xgb.XGBClassifier(**params)

    model.fit(
        X_train, y_train,
        eval_set=[(X_val, y_val)],
        verbose=False
    )

    # Optimize PR-AUC
    val_preds = model.predict_proba(X_val)[:, 1]
    pr_auc = average_precision_score(y_val, val_preds)

    return pr_auc
```

[ ]:

```python
# Create & run Optuna study

optuna.logging.set_verbosity(optuna.logging.INFO)
```

```
study = optuna.create_study(direction="maximize")

study.optimize(
    objective,
    n_trials=30,
    show_progress_bar=True
)
```

```
[I 2025-12-16 05:15:15,986] A new study created in memory with name: no-
name-e18a531f-ce6a-4e76-a7e2-61f84c90b6d3

  0%|          | 0/30 [00:00<?, ?it/s]

[I 2025-12-16 05:15:58,338] Trial 0 finished with value: 0.9372741594799279 and
parameters: {'n_estimators': 715, 'max_depth': 6, 'learning_rate':
0.02168449052947479, 'subsample': 0.9083193071086999, 'colsample_bytree':
0.530433310524615, 'min_child_weight': 10, 'gamma': 0.037865059361618644,
'reg_alpha': 0.24903190763196104, 'reg_lambda': 0.13901354504124674}. Best is
trial 0 with value: 0.9372741594799279.
[I 2025-12-16 05:16:28,601] Trial 1 finished with value: 0.9348217015540359 and
parameters: {'n_estimators': 505, 'max_depth': 3, 'learning_rate':
0.04252935617183846, 'subsample': 0.8548830200099582, 'colsample_bytree':
0.9571383883696744, 'min_child_weight': 5, 'gamma': 0.03984388270407086,
'reg_alpha': 0.5080949213925754, 'reg_lambda': 0.2806511346347993}. Best is
trial 0 with value: 0.9372741594799279.
[I 2025-12-16 05:16:56,478] Trial 2 finished with value: 0.9350527378738066 and
parameters: {'n_estimators': 648, 'max_depth': 4, 'learning_rate':
0.01551840624988376, 'subsample': 0.61890434826411, 'colsample_bytree':
0.9294532152763098, 'min_child_weight': 5, 'gamma': 0.08012142709781123,
'reg_alpha': 0.8703311043741734, 'reg_lambda': 0.10014736856348316}. Best is
trial 0 with value: 0.9372741594799279.
[I 2025-12-16 05:17:27,056] Trial 3 finished with value: 0.9364752240078973 and
parameters: {'n_estimators': 623, 'max_depth': 5, 'learning_rate':
0.01945215186461371, 'subsample': 0.679470345161981, 'colsample_bytree':
0.8118824043879238, 'min_child_weight': 6, 'gamma': 0.25987233183477265,
'reg_alpha': 0.8935027044297714, 'reg_lambda': 0.912931727954036}. Best is trial
0 with value: 0.9372741594799279.
[I 2025-12-16 05:18:17,082] Trial 4 finished with value: 0.9369783181044118 and
parameters: {'n_estimators': 847, 'max_depth': 7, 'learning_rate':
0.013358003524258857, 'subsample': 0.6263266995679763, 'colsample_bytree':
0.5220570921518173, 'min_child_weight': 5, 'gamma': 0.057322205673525035,
'reg_alpha': 0.9924758339175528, 'reg_lambda': 0.591176408518987}. Best is trial
0 with value: 0.9372741594799279.
[I 2025-12-16 05:18:50,438] Trial 5 finished with value: 0.9354353875762629 and
parameters: {'n_estimators': 532, 'max_depth': 6, 'learning_rate':
0.024038644533515178, 'subsample': 0.9941485649074983, 'colsample_bytree':
0.8100839543830314, 'min_child_weight': 3, 'gamma': 0.03368762916070673,
```

'reg_alpha': 0.5965124342423038, 'reg_lambda': 0.05977077129229458}. Best is trial 0 with value: 0.9372741594799279.
[I 2025-12-16 05:19:14,531] Trial 6 finished with value: 0.9352797386577635 and parameters: {'n_estimators': 655, 'max_depth': 4, 'learning_rate': 0.05424827418252879, 'subsample': 0.6914661123435303, 'colsample_bytree': 0.545300390756948, 'min_child_weight': 7, 'gamma': 0.28137344984233303, 'reg_alpha': 0.3573383691472325, 'reg_lambda': 0.13639328771912473}. Best is trial 0 with value: 0.9372741594799279.
[I 2025-12-16 05:19:36,021] Trial 7 finished with value: 0.9355534116757105 and parameters: {'n_estimators': 596, 'max_depth': 3, 'learning_rate': 0.07881381485271069, 'subsample': 0.6072609038909005, 'colsample_bytree': 0.7117279210703158, 'min_child_weight': 2, 'gamma': 0.06358197255809042, 'reg_alpha': 0.3808404954836563, 'reg_lambda': 0.057991456372852745}. Best is trial 0 with value: 0.9372741594799279.
[I 2025-12-16 05:20:16,204] Trial 8 finished with value: 0.936061730634012 and parameters: {'n_estimators': 459, 'max_depth': 7, 'learning_rate': 0.023838441093786345, 'subsample': 0.8799926304687533, 'colsample_bytree': 0.9093428216824049, 'min_child_weight': 2, 'gamma': 0.06627221815711477, 'reg_alpha': 0.7365413780344413, 'reg_lambda': 0.19418552969077418}. Best is trial 0 with value: 0.9372741594799279.
[I 2025-12-16 05:20:38,641] Trial 9 finished with value: 0.9322260099959316 and parameters: {'n_estimators': 456, 'max_depth': 3, 'learning_rate': 0.017520933903391538, 'subsample': 0.6801187354673235, 'colsample_bytree': 0.7720987492733464, 'min_child_weight': 4, 'gamma': 0.25554238578205096, 'reg_alpha': 0.48802796936808124, 'reg_lambda': 0.3621699371322413}. Best is trial 0 with value: 0.9372741594799279.
[I 2025-12-16 05:21:19,345] Trial 10 finished with value: 0.9355104450615548 and parameters: {'n_estimators': 815, 'max_depth': 6, 'learning_rate': 0.010012812293909315, 'subsample': 0.9996097618304924, 'colsample_bytree': 0.666838097993733, 'min_child_weight': 10, 'gamma': 0.1508212774199268, 'reg_alpha': 0.03499388881609175, 'reg_lambda': 0.5374918133674288}. Best is trial 0 with value: 0.9372741594799279.
[I 2025-12-16 05:22:06,017] Trial 11 finished with value: 0.9374294305773042 and parameters: {'n_estimators': 847, 'max_depth': 7, 'learning_rate': 0.010488910276083377, 'subsample': 0.7781666864684387, 'colsample_bytree': 0.5017387586697747, 'min_child_weight': 9, 'gamma': 0.12590293103128133, 'reg_alpha': 0.16983989495785132, 'reg_lambda': 0.6660305646719671}. Best is trial 11 with value: 0.9374294305773042.
[I 2025-12-16 05:22:44,357] Trial 12 finished with value: 0.9367928874564293 and parameters: {'n_estimators': 753, 'max_depth': 6, 'learning_rate': 0.010569746660378933, 'subsample': 0.7875713999289156, 'colsample_bytree': 0.6137192078807203, 'min_child_weight': 10, 'gamma': 0.14785066385757206, 'reg_alpha': 0.09158896058327112, 'reg_lambda': 0.7471045897534385}. Best is trial 11 with value: 0.9374294305773042.
[I 2025-12-16 05:23:12,273] Trial 13 finished with value: 0.9357349430190292 and parameters: {'n_estimators': 320, 'max_depth': 7, 'learning_rate': 0.030898536637635424, 'subsample': 0.7951289511285674, 'colsample_bytree': 0.501434774912186, 'min_child_weight': 8, 'gamma': 0.12994936456179929,

'reg_alpha': 0.19331163214683564, 'reg_lambda': 0.7090198848769962}. Best is trial 11 with value: 0.9374294305773042.
[I 2025-12-16 05:23:39,079] Trial 14 finished with value: 0.9365429471775564 and parameters: {'n_estimators': 898, 'max_depth': 6, 'learning_rate': 0.03542846615334513, 'subsample': 0.9222901328633399, 'colsample_bytree': 0.5987396285638087, 'min_child_weight': 9, 'gamma': 0.0009307262510564254, 'reg_alpha': 0.21003928193882965, 'reg_lambda': 0.39046853850162294}. Best is trial 11 with value: 0.9374294305773042.
[I 2025-12-16 05:24:09,803] Trial 15 finished with value: 0.9360225519059417 and parameters: {'n_estimators': 729, 'max_depth': 5, 'learning_rate': 0.013015076361075191, 'subsample': 0.7557644195482658, 'colsample_bytree': 0.5999348408991961, 'min_child_weight': 8, 'gamma': 0.11597263818850846, 'reg_alpha': 0.2548500561732207, 'reg_lambda': 0.9926712519781408}. Best is trial 11 with value: 0.9374294305773042.
[I 2025-12-16 05:24:43,254] Trial 16 finished with value: 0.9364766128294032 and parameters: {'n_estimators': 748, 'max_depth': 7, 'learning_rate': 0.0242266980798638, 'subsample': 0.8531516324198396, 'colsample_bytree': 0.6594965804773516, 'min_child_weight': 9, 'gamma': 0.19810185391929835, 'reg_alpha': 0.12215362581979913, 'reg_lambda': 0.7071818297230948}. Best is trial 11 with value: 0.9374294305773042.
[I 2025-12-16 05:25:05,186] Trial 17 finished with value: 0.9345837362992232 and parameters: {'n_estimators': 814, 'max_depth': 6, 'learning_rate': 0.05900879257355573, 'subsample': 0.9319120388098222, 'colsample_bytree': 0.5672155950322028, 'min_child_weight': 7, 'gamma': 0.19255064124251026, 'reg_alpha': 0.321206291857113, 'reg_lambda': 0.3783781916372417}. Best is trial 11 with value: 0.9374294305773042.
[I 2025-12-16 05:25:39,462] Trial 18 finished with value: 0.9364202291609299 and parameters: {'n_estimators': 900, 'max_depth': 5, 'learning_rate': 0.012683313490295283, 'subsample': 0.7392775015072733, 'colsample_bytree': 0.6634369969367555, 'min_child_weight': 10, 'gamma': 0.09751242292562803, 'reg_alpha': 0.4665095341654215, 'reg_lambda': 0.8210099899056966}. Best is trial 11 with value: 0.9374294305773042.
[I 2025-12-16 05:26:00,124] Trial 19 finished with value: 0.9338258441996994 and parameters: {'n_estimators': 706, 'max_depth': 7, 'learning_rate': 0.09611075368654973, 'subsample': 0.9185536219343036, 'colsample_bytree': 0.5505155071802217, 'min_child_weight': 8, 'gamma': 0.0033131380175129357, 'reg_alpha': 0.009248302271127024, 'reg_lambda': 0.5970720902401128}. Best is trial 11 with value: 0.9374294305773042.
[I 2025-12-16 05:26:36,955] Trial 20 finished with value: 0.9371021205330574 and parameters: {'n_estimators': 789, 'max_depth': 6, 'learning_rate': 0.01949009674192604, 'subsample': 0.8253912539059383, 'colsample_bytree': 0.7146762513955669, 'min_child_weight': 9, 'gamma': 0.1904153046711136, 'reg_alpha': 0.14547027234718146, 'reg_lambda': 0.45471040830343024}. Best is trial 11 with value: 0.9374294305773042.
[I 2025-12-16 05:27:13,235] Trial 21 finished with value: 0.9370591897634273 and parameters: {'n_estimators': 802, 'max_depth': 6, 'learning_rate': 0.0182338599007168, 'subsample': 0.8334505533543947, 'colsample_bytree': 0.7217281427827079, 'min_child_weight': 9, 'gamma': 0.19397629417411294,

```
'reg_alpha': 0.13795634717265642, 'reg_lambda': 0.4729234193061368}. Best is
trial 11 with value: 0.9374294305773042.
[I 2025-12-16 05:27:46,026] Trial 22 finished with value: 0.9369137091867801 and
parameters: {'n_estimators': 696, 'max_depth': 6, 'learning_rate':
0.029850359439610452, 'subsample': 0.8274671847454287, 'colsample_bytree':
0.8584986907633966, 'min_child_weight': 9, 'gamma': 0.2270379223611531,
'reg_alpha': 0.270887629184551, 'reg_lambda': 0.23810895172855745}. Best is
trial 11 with value: 0.9374294305773042.
[I 2025-12-16 05:28:30,286] Trial 23 finished with value: 0.936798597845538 and
parameters: {'n_estimators': 846, 'max_depth': 7, 'learning_rate':
0.015506315667671088, 'subsample': 0.8887638946060581, 'colsample_bytree':
0.5003223824740309, 'min_child_weight': 7, 'gamma': 0.1796391823403856,
'reg_alpha': 0.16516754267956285, 'reg_lambda': 0.4508774224331712}. Best is
trial 11 with value: 0.9374294305773042.
[I 2025-12-16 05:29:00,208] Trial 24 finished with value: 0.9368318613173219 and
parameters: {'n_estimators': 782, 'max_depth': 5, 'learning_rate':
0.020464231582004208, 'subsample': 0.7444616855713704, 'colsample_bytree':
0.6329258823544948, 'min_child_weight': 10, 'gamma': 0.15783863282144875,
'reg_alpha': 0.06951177638440503, 'reg_lambda': 0.6137773046070998}. Best is
trial 11 with value: 0.9374294305773042.
[I 2025-12-16 05:29:35,155] Trial 25 finished with value: 0.9363468925101102 and
parameters: {'n_estimators': 682, 'max_depth': 6, 'learning_rate':
0.028678051062615412, 'subsample': 0.7864444848065757, 'colsample_bytree':
0.9979603751001678, 'min_child_weight': 8, 'gamma': 0.1089104659251107,
'reg_alpha': 0.41528201983111696, 'reg_lambda': 0.28555990004908494}. Best is
trial 11 with value: 0.9374294305773042.
[I 2025-12-16 05:30:03,345] Trial 26 finished with value: 0.9345867349701737 and
parameters: {'n_estimators': 850, 'max_depth': 7, 'learning_rate':
0.037003379004222625, 'subsample': 0.959343413203855, 'colsample_bytree':
0.5713324884792619, 'min_child_weight': 1, 'gamma': 0.22107626750501563,
'reg_alpha': 0.2880586705350694, 'reg_lambda': 0.8235273963212846}. Best is
trial 11 with value: 0.9374294305773042.
[I 2025-12-16 05:30:35,429] Trial 27 finished with value: 0.935900576149212 and
parameters: {'n_estimators': 580, 'max_depth': 6, 'learning_rate':
0.011512930474043639, 'subsample': 0.8213977825459616, 'colsample_bytree':
0.6924003602673292, 'min_child_weight': 9, 'gamma': 0.1705951767528355,
'reg_alpha': 0.2051822467351066, 'reg_lambda': 0.6586939968881622}. Best is
trial 11 with value: 0.9374294305773042.
[I 2025-12-16 05:31:08,547] Trial 28 finished with value: 0.9349764730263699 and
parameters: {'n_estimators': 768, 'max_depth': 4, 'learning_rate':
0.01541163679767589, 'subsample': 0.8849602160793348, 'colsample_bytree':
0.7696284984732786, 'min_child_weight': 6, 'gamma': 0.0943944207401494,
'reg_alpha': 0.6108136355765934, 'reg_lambda': 0.5258599113203793}. Best is
trial 11 with value: 0.9374294305773042.
[I 2025-12-16 05:31:37,274] Trial 29 finished with value: 0.9368788604962388 and
parameters: {'n_estimators': 872, 'max_depth': 5, 'learning_rate':
0.026121397220229384, 'subsample': 0.8589048766221639, 'colsample_bytree':
0.5264995904900439, 'min_child_weight': 10, 'gamma': 0.021958502457426116,
```

'reg_alpha': 0.584303427137211, 'reg_lambda': 0.3092523460663027}. Best is trial 11 with value: 0.9374294305773042.

[ ]:
```
print("Best PR-AUC:", study.best_value)
print("Best Params:")
for k, v in study.best_params.items():
    print(f"{k}: {v}")
```

```
Best PR-AUC: 0.9374294305773042
Best Params:
n_estimators: 847
max_depth: 7
learning_rate: 0.010488910276083377
subsample: 0.7781666864684387
colsample_bytree: 0.5017387586697747
min_child_weight: 9
gamma: 0.12590293103128133
reg_alpha: 0.16983989495785132
reg_lambda: 0.6660305646719671
```

### 1.6.4 Final model

[33]:
```
X_train_full = pd.concat([X_train, X_val])
y_train_full = pd.concat([y_train, y_val])
```

[34]:
```
final_model = xgb.XGBClassifier(
    **study.best_params,
    objective="binary:logistic",
    tree_method="hist",
    device="cuda",
    random_state=42
)
```

[35]:
```
final_model.fit(X_train_full, y_train_full)
```

[35]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=0.5017387586697747, device='cuda',
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric=None, feature_types=None, feature_weights=None,
              gamma=0.12590293103128133, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.010488910276083377,
              max_bin=None, max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=7, max_leaves=None,
              min_child_weight=9, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=847, n_jobs=None,
              num_parallel_tree=None, …)
```

[36]:
```
from sklearn.metrics import roc_auc_score, average_precision_score

# probabilities
test_preds = final_model.predict_proba(X_test)[:, 1]

print("Test PR-AUC  :", average_precision_score(y_test, test_preds))
print("Test ROC-AUC :", roc_auc_score(y_test, test_preds))
```

```
Test PR-AUC  : 0.936344856462808
Test ROC-AUC : 0.7570527539132316
```

[37]:
```
from sklearn.metrics import (
    accuracy_score,
    precision_score,
    recall_score,
    f1_score,
    confusion_matrix,
    classification_report
)

for threshold in [0.5,0.6,0.7,0.8]:
  y_pred = (test_preds >= threshold).astype(int)

  # metrics
  metrics = {
      "Accuracy"  : accuracy_score(y_test, y_pred),
      "Precision" : precision_score(y_test, y_pred),
      "Recall"    : recall_score(y_test, y_pred),
      "F1-score"  : f1_score(y_test, y_pred)
  }

  # print metrics
  print('-'*60)
  print(f"For {threshold} Threshold")
  print('-'*60)
  for k, v in metrics.items():
      print(f"{k:<12}: {v:.4f}")

  # confusion matrix
  print("Confusion Matrix:")
  print(confusion_matrix(y_test, y_pred))

  # classification report
  print("Classification Report:")
  print(classification_report(y_test, y_pred))
```

```
------------------------------------------------------------
For 0.5 Threshold
```

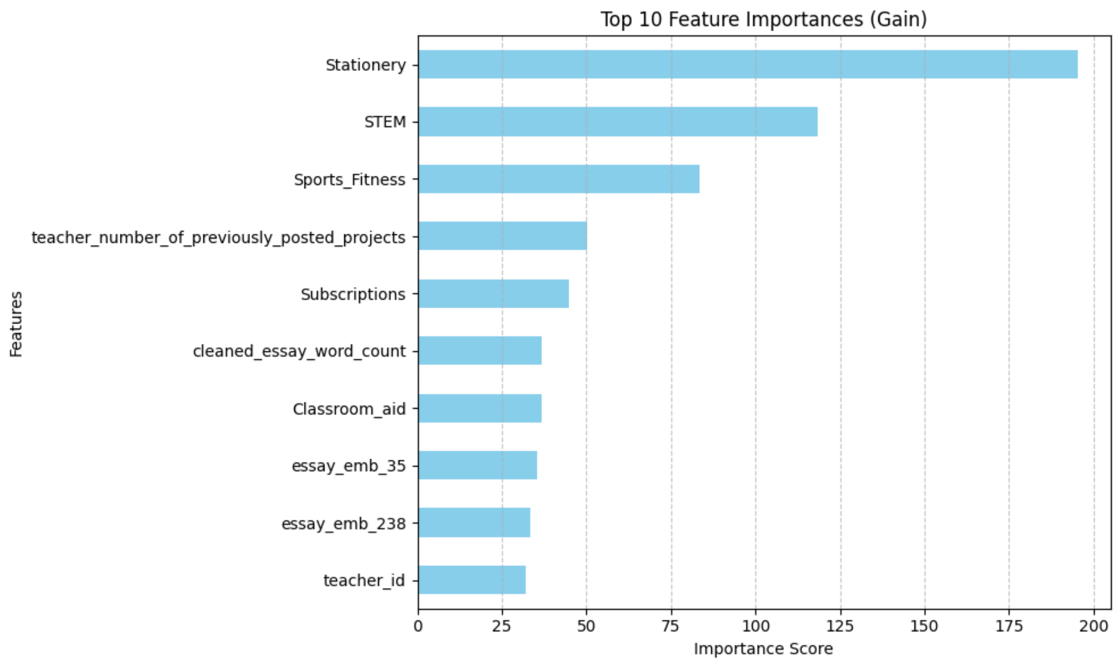
```
------------------------------------------------------------
Accuracy    : 0.8538
Precision   : 0.8584
Recall      : 0.9912
F1-score    : 0.9200
Confusion Matrix:
[[  277  3032]
 [  163 18378]]
Classification Report:
              precision    recall  f1-score   support

           0       0.63      0.08      0.15      3309
           1       0.86      0.99      0.92     18541

    accuracy                           0.85     21850
   macro avg       0.74      0.54      0.53     21850
weighted avg       0.82      0.85      0.80     21850

------------------------------------------------------------
For 0.6 Threshold
------------------------------------------------------------
Accuracy    : 0.8541
Precision   : 0.8687
Recall      : 0.9755
F1-score    : 0.9190
Confusion Matrix:
[[  575  2734]
 [  454 18087]]
Classification Report:
              precision    recall  f1-score   support

           0       0.56      0.17      0.27      3309
           1       0.87      0.98      0.92     18541

    accuracy                           0.85     21850
   macro avg       0.71      0.57      0.59     21850
weighted avg       0.82      0.85      0.82     21850

------------------------------------------------------------
For 0.7 Threshold
------------------------------------------------------------
Accuracy    : 0.8422
Precision   : 0.8833
Recall      : 0.9380
F1-score    : 0.9098
Confusion Matrix:
[[ 1011  2298]
 [ 1149 17392]]
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.47      0.31      0.37      3309
           1       0.88      0.94      0.91     18541

    accuracy                           0.84     21850
   macro avg       0.68      0.62      0.64     21850
weighted avg       0.82      0.84      0.83     21850

------------------------------------------------------------
For 0.8 Threshold
------------------------------------------------------------
Accuracy    : 0.7897
Precision   : 0.9066
Recall      : 0.8386
F1-score    : 0.8713
Confusion Matrix:
[[ 1707  1602]
 [ 2993 15548]]
Classification Report:
              precision    recall  f1-score   support

           0       0.36      0.52      0.43      3309
           1       0.91      0.84      0.87     18541

    accuracy                           0.79     21850
   macro avg       0.63      0.68      0.65     21850
weighted avg       0.82      0.79      0.80     21850
```

- We need to choose a threshold that **balances approvals with risk control**, not just maximizes recall
- In our case, **0.7 is best** because it **reduces false approvals** while still keeping recall reasonably high
- Thresholds **0.5 and 0.6 fail** because they **over-approve projects**, leading to many false positives
- Higher threshold **0.8 fails** by being too strict and missing a large number of genuinely good projects

[46]:
```python
# feature importances
feat_importances = pd.Series(final_model.get_booster().
 ↪get_score(importance_type='gain')).sort_values(ascending=True)

top_10_features = feat_importances.tail(10)

plt.figure(figsize=(10, 6))
top_10_features.plot(kind='barh', color='skyblue')
```

```python
plt.title('Top 10 Feature Importances (Gain)')
plt.xlabel('Importance Score')
plt.ylabel('Features')
plt.grid(axis='x', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```




- Stationery and STEM-related resource features dominate the model's gain-based importance, indicating that what is being requested (resource type and cost profile) has a stronger influence on approval outcomes than most textual or temporal features.

# 2 Insights and Recommendations

## 2.1 Insights

1. The dataset is **highly imbalanced** (~85% approvals), making PR-AUC more reliable than accuracy or ROC-AUC.
2. **Teacher behavior dominates approval outcomes**, but raw `teacher_id` cannot be used due to leakage.
3. **Aggregated teacher history features** are critical for generalization.
4. Teacher experience correlates with approval, but the **effect size is weak**, limiting standalone usefulness.
5. Low-cardinality features (teacher_prefix, grade) are encoded using **one-hot encoding**.
6. High-cardinality features (teacher_id, school_state) require **Stratified K-Fold target encoding** to avoid leakage.
7. Resource requests are **sparse**, with most projects focusing on 1–2 resource types.

8. **Books and Stationery dominate** approvals, reflecting essential classroom needs.
9. High-cost categories (STEM, Electronics) show **lower approval likelihood**.
10. Project cost and quantity are **right-skewed** and benefit from **log transformation or binning**.
11. Temporal features show strong seasonality but **negligible causal impact** on approval.
12. Text features (title, essay) are **high-dimensional and mostly unique**, favoring TF-IDF or embeddings.
13. Sentiment and readability show **statistical significance but weak practical value**.
14. **XGBoost is well-suited** due to its ability to handle non-linearity, sparse features, and mixed data types.
15. Class imbalance is addressed using **scale_pos_weight = 0.178**, improving minority-class learning.
16. Hyperparameter tuning via Optuna achieved **Best PR-AUC 0.937**, indicating strong ranking performance.
17. Optimized parameters (deep trees, low learning rate, regularization) show a **bias–variance balanced model**.
18. **Consistent PR-AUC across train, validation, and test** confirms minimal overfitting.
19. ROC-AUC (~0.76) is lower due to imbalance, reinforcing why **PR-AUC is the primary metric**.
20. **Decision threshold = 0.7** provides the best balance between approval volume and risk by reducing false approvals without excessive recall loss.
21. **Stationery** and **STEM**-related resource features dominate the model's gain-based importance, indicating that **what is being requested (resource type and cost profile)** has a stronger influence on approval outcomes than most textual or temporal features.

## 2.2 Recommendations

1. **Adopt a risk-based approval workflow**

   → *Impact:* Reduces reviewer load by focusing effort only where risk is high.

2. **Operationalize model threshold at 0.7, however recalibrate the model and threshold periodically**

   → *Impact:* Lowers false approvals while preserving high approval throughput.

3. **Fast-track low-risk projects automatically**

   → *Impact:* Shorter approval cycle times and better teacher satisfaction.

4. **Escalate high-cost and complex requests for deeper review**

   → *Impact:* Better capital allocation and reduced funding risk.

5. **Introduce cost-optimization nudges during project creation**

   → *Impact:* Increases approval likelihood and overall platform efficiency.

6. **Avoid policy rules based on submission timing or seasonality**

   → *Impact:* Prevents ineffective operational constraints with no approval benefit.

7. **Base decisions on aggregated teacher behavior, not identity**

→ *Impact:* Improves fairness, scalability, and model generalization.

8. **Standardize reviewer decisions using model risk scores**

   → *Impact:* Reduces inconsistency and subjective bias across reviewers.

9. **Track false approvals and PR-AUC as core KPIs**

   → *Impact:* Aligns monitoring with real business risk instead of inflated accuracy.

10. **Introduce resource-aware review prioritization**

    → *Impact:* Enables faster approvals for low-risk, essential resource requests (e.g., stationery) while flagging high-cost or complex categories (e.g., STEM) for closer review.